THE ECOLOGICAL CUMULATIVE RISK MODEL

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This paper provides a theoretical and empirical introduction to the Ecological Cumulative Risk Model, an alternative to traditional additive models of cumulative risk (CR). The model is based upon Bronfenbrenner's Ecological Systems Theory (Bronfenbrenner, 1979) which posits that development occurs across a number of settings, each with varying proximity to the child. The model is intended as a compromise between additive and multiplicative measurement models of risk. Using the NICHD Study of Early Child Care and Youth Development I categorize a number of risk factors into one of six settings (i.e. demographic, parenting, neighborhood). Factor analysis is used to validate the underlying structure of these groupings. All risk factors were determined from 3rd grade measures and prior while all outcome variables (academic skills, externalizing behaviors, internalizing behaviors, and social skills) were measured at 4th grade. The predictive power of these settings/domains was contrasted against the predictive power of a traditional cumulative risk model. Thus, a total CR score within each setting was calculated as well as an overall CR score. Results indicate that the Ecological CR Model explains approximately 1% more variance across dependent variables compared to the traditional/overall approach. An advantage of dividing risk factors into domains is the ability to model interaction effects, even when using a cumulative risk measurement model. Of the thirty interaction effects that were tested, only two were statistically significant. Finally, structural equation modeling was used to validate the Ecological Domains Model.

SEM analyses confirmed that the Ecological Cumulative Risk Model fit the data better than a lump sum approach. Furthermore, evidence of mediation through risk domains is provided; parenting risk partially mediates the effects of demographic risk on all outcome variables. I conclude that the Ecological Cumulative Risk Model is valuable for examining the processes through which risk operates (i.e. proximal domains mediate the impact of more distal risk domains). On the other hand, lack of interaction effects suggests that an additive approach is more viable than a multiplicative model. More research, particularly with a higher risk sample, is needed to further understand the utility of this measurement model.

BIOGRAPHICAL SKETCH

Sara Sepanski Whipple entered the Human Development graduate program at Cornell University in Fall 2005 after completing a Masters degree in Psychology at the University of Richmond. She grew up in central New York, the daughter of two devoted teachers who undeniably influenced her career pursuits. After high school Sara attended Wake Forest University where she majored in psychology. While at Cornell, Sara worked closely with Dr. Gary Evans and Dr. Marianella Casasola. Her research interests include the effects of poverty and risk on developmental outcomes, particularly academic achievement. Sara aims to teach at a liberal arts college where she can continue her research pursuits. Currently she lives in rural Virginia with her husband, David, dog, Junebug….and a baby on the way.

Dedicated to my Great Aunt Mary.

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INTRODUCTION

Children live, learn, and adapt across a variety of settings. While the family is the most commonly studied of these contexts, school, neighborhood, and even peer environments also directly influence children's development (Boyce et al., 1998; Coie et al., 1993; Eamon, 2001; Hawkins, Arthur, & Catalano, 1995; Huston & Bentley, 2010; Pollard, Hawkins, & Arthur, 1999). A large history of research has demonstrated that individual risk factors within each of these domains are associated with maladaptive psychological functioning. A common difficulty with this type of research is that the processes to be investigated are complex, yet the resources for collecting adequate amounts of data are limited. When sample sizes are small it is nearly impossible to effectively model the contributions of multiple individual risk factors and how they interact to affect development. Even simple regression techniques are limited with small sample sizes.

Due to these limitations cumulative risk (CR) models have become popular for their theoretical, practical, and statistical strengths. These cumulative models of risk have provided evidence for the synergistic effects of multiple simultaneous risk factors (Kolvin, Miller, Fleeting, & Kolvin, 1988, Rutter, 1979, Sameroff, Seifer, Barocas, Zax, & Greenspan, 1987; Werner & Smith, 1977). Despite their strengths, one of the most common criticisms of CR models is the assumption that all risks can be lumped into one overall index, disregarding not only the type of risk but its proximity to the child and the setting of its occurrence. This assumption creates a further drawback, the inability to model interaction effects between variables. It is these limitations of CR models that motivated me to re-conceptualize how multiple risks could be studied.

The goal of this paper is to extend traditional CR research such that interaction effects and mediation might be incorporated. I do this by examining how risk operates across multiple contexts in which a child resides and by challenging the additivity assumption implicit to traditional CR models. Briefly stated, this assumption presumes that risk factors operate independently of each other such that multiplicative effects of risk do not occur. In this paper I propose a new methodology for understanding the potential interaction of risks across multiple settings. The methodology is guided by Bronfenbrenner's bioecological model of development (1979; 1986; Bronfenbrenner & Morris, 2006), which posits that various contexts affect children's development. While some of these processes exert direct influences on the child (proximal processes, i.e., parenting), others act more indirectly (distal processes, i.e., household income). Using this type of ecological model of development allows me to categorize risk into different domains; by doing so it is possible to test for interaction effects and mediation, even with a CR model.

What follows is a review of the theory guiding this new methodological framework. I begin by examining how risk has historically been studied. Next I discuss the contributions of cumulative risk methodology as well as its limitations. In order to provide a rationale for the current study, I review the handful of recent studies suggesting that risk may not simply be additive in nature. The principles of Bronfenbrenner's theoretical model of human development are reviewed in order to frame the domain specific approach I use. I spend the remainder of the paper proposing a study to empirically validate my proposed model, hereafter referred to as the Ecological Cumulative Risk Model. I use this model to assess the cumulative effects of risk across various ecological domains in a child's life.

Defining Risk and Understanding Its History in Psychological Research

To begin it is essential to understand risk in general and why it has become such a growing area of inquiry. Risk research has its roots in epidemiology and medicine as it attempts to identify those factors "that accentuate or inhibit disease and deficiency states and the processes that underlie them" (Garmezy, 1994, p. 9). A risk factor is perhaps best defined as an influence that increases the probability of harm, contributes to a more serious state, or maintains or increases a problem condition (Coie et al., 1993). While all risk factors are predictive, it is important to point out that not all are causal (Coie et al., 1993; Pollard et al., 1999; Serbin & Karp, 2004). A risk factor can only be deemed causal if when changed it also produces a change in the outcome (Kraemer, Stice, Kazdin, Offord, & Kupfer, 2001).

Arguably central to the study of risk is the belief that if stressors can be identified, intervention is possible, and the likelihood of developing a specific maladaptive outcome can be reduced. Moreover, societal payoffs are greatest if efforts are concentrated on identifying those risk factors that are common to many disorders (Coie et al., 1993; Sameroff, Seifer, & McDonough, 2004). If a constellation of generic risks can be recognized and altered, thereby reducing maladaptive outcomes, the need for health, social, and correctional services can be reduced (Coie et al., 1993).

Risk can occur both within and outside of a person to impact health, psychological well-being, and social performance (Jessor, Van Den Bos, Vanderryn, Costa, & Turbin, 1995). Some investigators categorize risk factors into domains. These include: demographic risk (i.e., race, income, single parent status), physical environmental risk (i.e., quality of home environment), parenting risk (i.e., maternal responsiveness), sociocultural risk (i.e., maternal age), psychosocial risk (i.e., negative life events), personal risk (i.e., temperament), biological risk (i.e., perinatal problems), peer risk (i.e., peer deviance), school risk (i.e., school connectedness), neighborhood risk (i.e., safety), and parental characteristics (i.e., education). As will be discussed subsequently, the issue of collapsing or not collapsing risk factors across domains is an important one.

Risk has been studied through case histories, cross-sectional short term studies, and longitudinal investigations (see Garmezy, 1994). Studies have been carried out from birth to adulthood using a wide range of risk factors. It is nowhere near possible to provide a comprehensive review of the psychological risk literature, but it is feasible to offer a general overview and evaluation of past methodologies.

Particular attention to risk emerged around the middle half of the 20th century, when scholars became interested in the origins of social and health problems. At that time the focus was on specific risk processes, such as the influence of parent-child attachment on childhood disorders (Fraser, Kirby, & Smokowski, 2004). The 1980s marked significant changes in the ways, and degree to which, risk was studied. The fields of developmental psychopathology and life course studies were emerging and research into childhood stress greatly increased. Investigators turned to large community samples, allowing them to examine a wide spectrum of stressors (Gore & Eckenrode, 1994). During this point in time risk tended to be operationalized using one of three approaches. First, specific life stresses such as parent divorce, institutionalization, war, economic deprivation, and parental psychopathology were common areas of study (Garmezy & Masten, 1994; Gore & Eckenrode, 1994; Luthar & Zigler, 1991). The purpose of this research was to understand how singular, critical events affected development. The second of these approaches, the life events methodology, followed from epidemiologic studies as it considered how the number of situational stressors was associated with physical and mental health. This approach to risk focused on how the accumulation of self-reported stressors put a person at risk for various maladaptive outcomes (Gore & Eckenrode, 1994). Lastly, the third technique focused less on major life events and more on the daily hassles experienced by individuals. Daily hassle research considered the more proximal influence of small but daily stresses that contributed to children's behavioral symptoms (Gore & Eckenrode, 1994; Luthar & Zigler, 1994).

Other investigations of risk processes in childhood have focused on broad indicators of risk, such as family SES, family composition, and parental mental health status. Fraser and colleagues (2004) refer to these types of environmental conditions affecting vulnerability as "contextual effects". Although these risk indices are indeed predictive of child disorder, dissatisfaction with this aggregation technique has emerged. For one, such global risk factors do not take the more proximal causes of disorder into account. A parent may be classified as mentally ill, but exactly how that mental illness affects the child differs widely across circumstances. Additionally, focusing on structural conditions is dangerous because of the large degree of covariation among risk factors (Gore & Eckenrode, 1994; Luthar & Zigler, 1991).

In response to the limitations of contextual risk models and mere additive approaches, researchers began examining the mediator and moderator effects of risk. This type of research uses a multidimensional perspective to understand how contexts work together to influence children's behavioral and emotional development (Boyce et al., 1998). For example, it is now commonly accepted that the effects of maternal education on child achievement are mediated by cognitive stimulation in the home (Bradley & Corwyn, 2002; Duncan & Brooks-Gunn, 1997). With regard to moderator effects, Ackerman and colleagues (Ackerman, Izard, Schoff, Youngstrom, & Kogos, 1999) have found that family instability and child temperament statistically interact, such that children with low temperamental adaptability who experience high levels of family instability are at heightened risk for developing internalizing problems. These types of analyses provide important information about both the proximity and setting of risk factors. For example, child temperament is an individual, highly proximal risk factor whereas maternal education is a more distal, socio-demographic risk factor.

Through its history risk research has identified numerous variables that predict developmental outcomes in various combinations. Among the major difficulties of such research is retaining statistical power when using large numbers of risk factors and adequately modeling the complex inter-relationships between variables. I intend to provide such a comprehensive approach through the Ecological Cumulative Risk Model.

Multiple Risk Models

Clearly, studying the manifestation of risk in child development is not straightforward. In order to better understand the myriad approaches to measure and analyze risk that researchers have used I present a review of multiple risk measurement models. Naturally, every approach has its advantages as well as its limitations. It is my goal to use the information presented here to create and validate a measurement model that maximizes advantages while minimizing limitations.

Multiple risk can be used an overarching term that encompasses any type of model with more than one predictor variable. At the broadest level, multiple risk models can be contrasted against single-risk factor models. Not surprisingly, a great deal of evidence supports the superiority of multiple risk models over single risk factor models (Coie et al., 1993; Luthar, 1993; Wachs, 2000).

Arguably, the most comprehensive way of measuring multiple risks is to include all predictor variables in a regression model. Continuous measures of each predictor retain information on the intensity of exposure such that the contribution of each variable can be assessed in relation to other predictors. In addition to understanding the impact of individual variables, multiple regression allows for the analysis of statistical interactions between combinations of variables. Unfortunately, interpretability and statistical concerns often prevent the researcher from modeling multiple risks in this manner. As a result of these challenges, several alternative models for measuring multiple risks have been examined. In Figure 1 I categorize these techniques based on their measurement models. It is not necessary to discuss all of these techniques for the purposes of this paper. However, I will focus on Figure 1 briefly in order to provide a prerequisite understanding of the assumptions, advantages, and disadvantages of various measurement models of multiple risks.

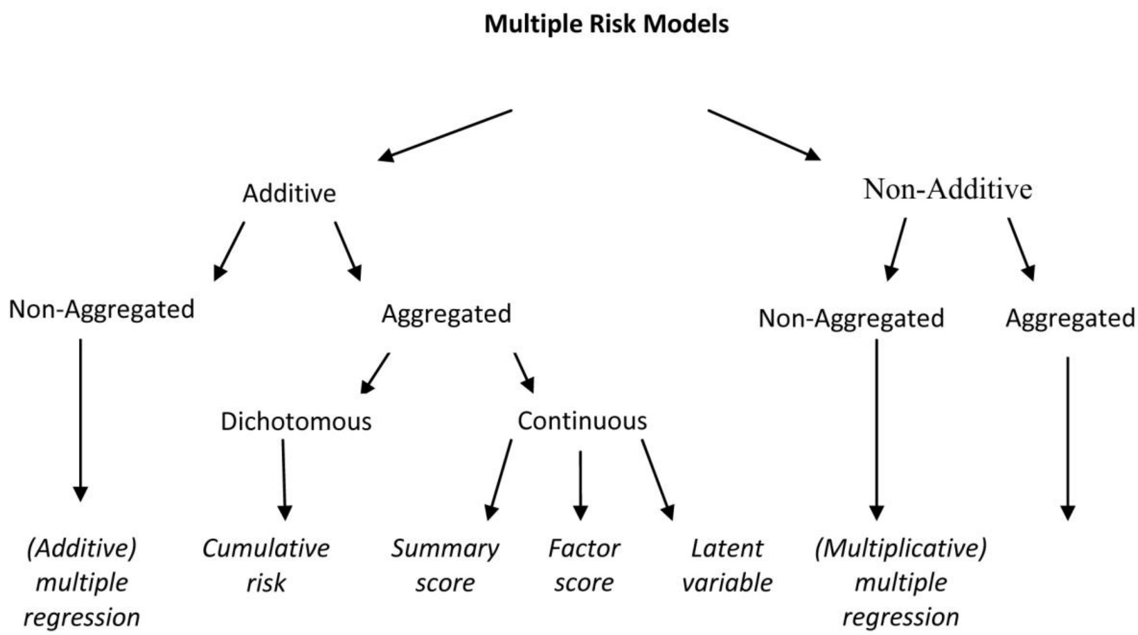

Figure 1. Types of multiple risk models.

Additive Versus Non-Additive Models

The first level of Figure 1 categorizes multiple risk models according to how risks are believed to affect to each other. If risk factors are presumed to operate independently of each other, an additive model is used (Whipple, 2010). Because additive models only examine main effects, they have the advantage of being easy to interpret. However, along with ease of interpretability comes a downside; additive models are restrictive, hypothesizing that the effects of each predictor variable occur independently of each other risk factor.

In contrast, non-additive, or multiplicative, models assume that there can be interactions between risks such that the effects of explanatory variables are disproportional or non-additive (Whipple, 2010). Non-additive models have the advantage of taking into account synergistic effects between risk factors. On the negative side, non-additive models tend to require very large sample sizes and can be difficult to interpret, particularly if higher order multiplicative terms are present.

Aggregated Versus Non-Aggregated Models

The second level of Figure 1 categorizes multiple risk models according to how risk factors are analyzed. Are they collapsed into an overall risk index or is the specificity of each singular risk variable preserved?

In a non-aggregated risk model, the type of risk and range of data are preserved. These models rest on the hypothesis that each risk factor has a unique impact on development apart from other predictors. Furthermore, some risks can be more predictive than others and the amount of exposure to these influential variables predicts developmental outcomes (Burchinal, Roberts, Hooper, & Zeisel, 2000; Pungello, Kupersmidt, Burchinal, & Patterson, 1996).

Because non-aggregated models are capable of narrowing in on the effects of specific explanatory variables, they have the advantage of aiding in intervention efforts by identifying the most potent risks in children's lives. Non-aggregated models are not without their disadvantages, however. Modeling multiple predictor variables alone can require a substantial sample size, let alone when interaction terms are present. Additionally, certain statistical assumptions, such as independence of multiple risk variables, must be met in order to obtain valid parameter estimates. Therefore if the risk variables are in fact collinear, this approach to modeling multiple risk is problematic

In contrast, aggregated risk models collapse risk into an overall index. By doing so, aggregated models avoid many of the problems inherent to non-aggregated risk models. Rather than focusing on the level of specific types of risk, aggregated models focus on the total amount of risk experienced by a person. Aggregated risk models do not provide information about particular risk variables; rather, they assume that regardless of the form of risk, it is the overall level of risk that affects developmental outcomes (Whipple, 2010). Thus, aggregated models have the advantage of avoiding problems of multicollinearity and substantial sample size. Furthermore, because data are collapsed, the overall predictor variables are more reliable. Aggregated techniques have been criticized for their inability to identity specific targets for intervention and for treating all risks equally.

Additive Models

On the left side of Figure 1 are the additive risk models. Under the non-aggregated branch is multiple regression. This technique preserves the type and intensity of multiple risks. It further assumes that the combined effect of the risk variables is equal to the sum of their separate effects. Recall that unlike the non-additive multiple regression technique, additive models assume risk factors do not interact. Because additive, non-aggregated models retain information about each risk variable, they have the advantage of identifying specific risk factors that contribute to developmental outcomes. For example, Gerard & Buehler (2004a) report that parent's educational status and household size are significant predictors of 7^{th}-12^{th} graders' internalizing problems, yet the same variables are not predictive of externalizing problems. Of all 14 risk factors the researchers examined, parental warmth was the best predictor for both outcomes. Furthermore, the regression coefficients of additive, non–aggregated risk models are straightforward and easy to interpret.

Depending on the number of risk variables in the model, additive, non-aggregated models can have the disadvantage of requiring large sample sizes. Additionally, because non-aggregated risks are often correlated to some degree, these models can be unreliable. If the correlations between predictors are moderate or high, parameter estimates can become deflated (Burchinal et al., 2000; Mosteller & Tukey, 1977). This is because regression coefficients reflect the degree to which an individual predictor variable contributes to the outcome after adjusting for the contributions of other predictors. It is entirely possible for a predictor variable to appear minimally related to the outcome if that same variable is highly correlated with another explanatory variable in the model. In fact, it is possible for the total model to explain a great deal of variance in the outcome, while no single variable is a significant predictor.

The middle portion of Figure 1 shows four additive, aggregated risk models, broken down according to *how* risks are defined, continuously or dichotomously. Continuous aggregation preserves the variability (continuous nature) of data, whereas dichotomous aggregate models assign a cut-off value for determining if risk is present or absent for each singular risk parameter. I focus only on the latent variable approach as it is the most relevant to the current study.

The latent variable or structural equation modeling (SEM) technique qualifies as an aggregate risk model since individual predictors are used to create a latent risk variable. Although least common at this point in time, latent variable models have the benefit of preserving continuous data and taking measurement error into account. A major downside of the technique is the large sample size required to model multiple indicators (Kline, 2005). Furthermore, it is much more complicated to test interaction effects between variables in latent models.

Finally, we come to the dichotomized aggregate model. Although terminology can be mixed, the vast majority of researchers refer to this dichotomization technique as cumulative risk and to its associated aggregate predictor as a cumulative risk index (Ackerman et al., 1999; Corapci, 2008; Evans, 2003; Forehand, Biggar, & Kotchick 1998; Gasman-Pines & Yoshikawa, 2006; Gerard & Buehler, 2004a, 2004b; Hooper, Burchinal, Roberts, Zeisel, & Neebe, 1998; Jessor et al., 1995; Klein & Forehand, 2000; Liaw & Brooks-Gunn, 1994; Li-Grining, 2007; Luster & McAdoo, 1994; Ostaszewski & Zimmerman, 2006; Pungello et al., 1996; Small & Luster, 1994; Stanton-Chapman, Chapman, Kaiser, & Hancock, 2004; Thornberry, Smith, & Howard, 1997; Yumoto, Jacobson, & Jacobson, 2008). Of all the multiple risk techniques, cumulative risk reduces data the most. Risk status on individual variables is identified via a statistical criterion (i.e., upper quartile equals risk) or a priori-determined criteria based on theory (i.e., single parent status is risk). The number of risks is then summed to create a cumulative risk index and this index is used to predict developmental outcomes. A major advantage of this approach is its ability to model multiple risks even in small sample sizes. Furthermore, because risk status is pre-defined there are no assumptions about the distribution of risk factors. Major disadvantages of cumulative risk include the potential subjectivity in assigning appropriate cut-off points for risk and the fact that all risks are treated equally. The remainder of this paper discusses these issues in depth.

Non-Additive Models

On the right side Figure 1 are two examples of non-additive models. Multiplicative linear regression is commonly used to examine non-additive, non-aggregated models. Recall that this model retains the range of data and the specificity of risk factors. Furthermore, it examines whether the relationship between a risk variable and the outcome depends on the value of another risk variable. Using a multiplicative model of this sort, Liaw & Brooks-Gunn (1994) found that family poverty interacted with both race and maternal verbal ability to affect child IQ scores. Being African American or Hispanic and having a mother with low verbal IQ had greater effects on child IQ for non-poor children than poor children. This non-additive, disaggregated model is very powerful and precise, but suffers from a very practical problem. As mentioned above, in order to model multiple predictors and detect interaction effects, an extremely large sample size is necessary. The example by Liaw and Brooks-Gunn consisted of three risk variables, but what if they had also wanted to examine other risk variables such as single parent status, teenage pregnancy, instability or family residence, and so on?

Clearly missing from Figure 1 is a non-additive, aggregated measurement model of multiple risks. Borrowing from the strengths of other multiple risk models I propose the Ecological CR Model to fill in this gap. I suggest that cumulative risk methodology along with an ecological development approach is one means of reconciling a number of the limitations of past risk research. In order to ground this proposed model theoretically I turn first to a more extensive review of cumulative risk methodology.

The Cumulative Risk Approach

As mentioned above, models of cumulative risk assume that the accumulation of risk factors, independent of the presence or absence of particular risk factors, has an impact on developmental outcomes. Specifically, the number of risk factors is positively associated with the likelihood of developing behavioral or clinical disorders (Rutter, 1979; Sameroff, 2000). In analyzing data from the Rochester Longitudinal Study Seifer & Sameroff (1987) showed that no single risk factor accounted for all of the significant variance in their outcome variable, child IQ. Furthermore, when the effect of any one risk factor was partialled out, the variance explained by the remaining risk index remained significant. Thus, a count of the total number of risks experienced by a child acted as the best predictor of IQ.

To create such an index, risk must be assigned to each predictor variable using a binary scale. Either a child experiences risk on that variable (1) or a child does not experience risk on that variable (0). While it is fairly straightforward to code dichotomous variables, assigning risk to variables measured on a continuous scale is slightly more subjective. Typically those scoring in the top 25% or 1 SD above the mean are at risk while the remainder of sample participants receive a score of 0 on that particular variable.

A key advantage to using the dichotomization approach of cumulative risk is that all variables are represented in one overall index. Subsequently, cumulative risk does not weight individual predictor variables; each risk factor is assumed to contribute to the outcome equally. This allows for more statistical power in testing outcomes and interactions because far fewer terms are entered into the regression equation. Thus, CR models are especially advantageous when dealing with small sample sizes because it is possible to consider several risk variables without compromising power. In fact, some studies have looked at up to 32 risk factors in one model (Fergusson, Horwood, & Lynskey, 1994).

An additional strength of CR models is their easy of interpretability compared to multiple regression models. Unstandardized beta values that result from CR model regressions can be interpreted on a simple basis because a one unit change in the independent variable is associated with a certain amount of change in the dependent variable. Thus, in the case of a linear model, an increase of one risk factor would produce a change of X (unstandardized beta amount) in the outcome.

One inherent flaw with interacting risk variables in a multiple regression model is that risk variables tend to show a high degree of multicollinearity. In other words, the predictor variables are highly related to one another and it is difficult to disentangle the effects of one variable from another. When a number of risks are collinear, statistical interactions do not occur. In fact, a relatively common occurrence in multiple risk regression models is to find a significant overall model, but few significant individual predictors. The result is a lack of true understanding as to what variables or processes are driving the outcome. Along these same lines, sample size requirements needed to test a number of statistical interactions often are not met. In effect, another advantage of cumulative risk models is their lack of multicollinearity.

Numerous studies have confirmed the relationship between cumulative risk and harmful outcomes (Burchinal et al., 2000; Deater-Deckard, Dodge., Bates, & Pettit, 1998; Gerard & Buehler, 1999, 2004a, 2004b; Kolvin et al., 1988; Rutter, 1979; Sameroff et al., 1987; Werner & Smith, 1977). Rutter's (1979) Isle of Wight and Inner City London epidemiologic studies act as the backbone of this research. As a child psychiatrist, Rutter was interested in the transmission of psychiatric disorder from one generation to the next. In his research he identified six family variables that were know to be associated with psychiatric disorder: severe marital discord, low social status, overcrowding, paternal criminality, maternal psychiatric disorder, and admission into the care of a local authority (Rutter & Quinton, 1977). When Rutter and colleagues separated children according to those who had zero, one, two, three, or four or more risk factors his results supported a curvilinear effect for the impact of number of risk factors on disorder. Specifically, the rates of psychiatric disorder of children who experienced zero risk factors were not significantly different from children who experienced one risk factor (both about 2%). However, when the number of risks jumped to two risk factors there was a significant change in prevalence of disorder (5%). When four or more risk factors occurred in combination the prevalence rate quadrupled (20%). Rutter concluded that the risks potentiated each other; additional stresses did not simply sum together in a linear combination, but they exacerbated each other.

In another seminal cumulative risk study, Kolvin and colleagues (1988) found that a six factor risk index significantly predicted the likelihood of engaging in each of six criminal offenses. The multiply deprived group, defined as those experiencing risk in two or more categories, had the highest number of convictions and the highest number of repeated offenses. Additionally there was no evidence that different types of deprivation were associated with distinct offenses. In other words, experiencing any combination of multiple risks led to a wide variety of outcomes.

Sameroff and colleagues have performed other influential work in this field (Sameroff, 1998; Sameroff et al., 1987; Sameroff, Seifer, Baldwin, & Baldwin, 1993). Using data from the Rochester Longitudinal Study these researchers followed an initial group of 215 children from birth to age 13. Ten correlates of SES were identified as risk factors: maternal mental health, maternal anxiety, parental perspectives, mother interactive behaviors, maternal education, head of household occupation, minority group status, father presence, family size, and stressful life events. For categorical variables such as education, minority group status, and father presence risk was assigned if the mother had not completed high school, the father was absent, and the child was of minority status. A quartile cut-off was used for most continuous variables; those scoring at the highest or lowest end (depending on scale) of the sample distribution were deemed at risk. A family size of four or more children was considered a risk factor.

Looking at 4-year-old IQ scores, the researchers found that the CR index significantly predicted IQ. As the number of risks increased, IQ test performance decreased. Not only that, but IQ scores dropped significantly after two risk factors. Compared to the single variable approach, the multiple risk approach resulted in a threefold increase in the magnitude of differences between groups. The average IQ of children with no risk factors was 118 while the average IQ score for children with 7 or 8 risk factors was 85. This is a range of two standard deviations. At ages 13 and 18 the same risks were used to calculate a new multiple risk score reflecting the current situation. Interestingly, few families showed major changes in the number of risk factors they had experienced. The multiple risk indices at age 4 and 13 respectively accounted for 34% and 37% of variance in child IQ (Sameroff et al., 1993).

Disadvantages of Cumulative Risk

Cumulative risk is not without its faults, the greatest of these being the minimization of information, the diversity in dichotomization approaches, and the fact that all risks are treated equally.

Minimization of Information

The dichotomization of variables inherent to CR models means that originally data-rich, continuous variables become binary indicators of risk. If seven risk variables are included in the model, data becomes condensed to one predictor variable with a range of 0 to 7. This is quite different from a non-aggregated approach in which the original scale of each variable is preserved and every variable is used to predict outcomes.

One of the reasons most CR models do not explain the same degree of variance as individual variable analyses is the lack of variability inherent to a dichotomized variable. If child IQ score were regressed on maternal mental health status, maternal education, and negative life events, the variance explained would likely be far more than if child IQ score were regressed on one risk index score with a range of 0 to 3.

Diversity in Dichotomization Approaches

Another drawback to the CR approach is the subjective nature of deeming what level of a variable makes it “risky”. Most studies rely merely on sample distributions to determine risk cut points. The most common cut points for continuous variables include the highest (or lowest) quartile or 1-1.5 standard deviations above (or below) the mean. The concern with such a subjective, sample-based approach is the lack of consistency across studies. While some studies include children from highly disadvantaged circumstances (Burchinal et al., 2000; Hooper et al., 1998; Jones, Forehand, Brody, & Armistead, 2002; Liaw & Brooks-Gunn, 1994; Shaw, Vondra, Hommerding, Keenan, & Dunn, 1994) other research uses more representative samples (Deater-Deckard et al., 1998; Fergusson et al., 1994; Gerard & Buehler, 2004a, 2004b; Sanson, Oberklaid, Pedlow, & Prior, 1991). A major effect of these different sample characteristics is that the cut point for risk variables wavers; for example, the cut point for being at risk on a negative life events variable in the former studies would be much higher than the cut point in the latter studies.

Although using quartiles or standard deviation cut points is a theoretically sound technique when used in isolation, the meaningfulness or risk gets blurred across studies with different sample characteristics. The 1 SD cut-off warrants special comment because the skewness of a variable’s distribution affects the amount of children deemed at risk on that variable. In a sense this technique can yield weighted risk variables. On the other hand, a 25% cut-off criteria weighs all risk variables equally.

All Risks Treated Equally

Cumulative risk models weigh risk factors equally so that the contribution of any risk variable is no more important than the next. However, from non-aggregated risk models we know that some variables are more influential in predicting developmental outcomes than other risk variables. For example, among 7th-12th graders, parental warmth is a strong predictor of externalizing problems, yet parent's educational status and household size are not significantly related to the same outcome (Gerard & Buehler, 2004a).

In a similar vein, cumulative risk studies not only weigh risk factors within the same ecological domain equally, but collapse various types of risk into one lump sum. Most studies reviewed here consider different areas of risk (i.e., child factors, family factors, home environment, neighborhood, etc.). However, variables within each of those domains are considered equal and thus their risk status is interchangeable in a total CR index. For example, Liaw and Brooks-Gunn (1994) examined at least one variable in each of the following domains when determining risk: biological, socioeconomic, maternal characteristics, family structural, and parenting beliefs. Despite different domains of risk being represented, the total CR score for a family was the sum across all variables in all domains. Other studies collapse across ecological contexts in the same way (Fergusson et al., 1994; Gerard & Buehler, 2004b; Greenberg, Speltz, DeKlyen, & Jones, 2001; Jessor et al., 1995; Lengua, 2002; Luster & McAdoo, 1994; Sanson et al., 1991). Although researchers often specify the type of risk involved for non CR models, when it comes to cumulative risk these domains become irrelevant.

Determining Variables and Difficulty Modeling Interactions

The inability to model interaction effects between risk variables highlights another disadvantage of the CR model. Measuring the correct number and type of relevant risk variables is a concern with all forms of human research since people are influenced by both known and unknown sources. However, because CR is limited by its additive, aggregated measurement of risk it can be particularly difficult to determine which variables to use in a CR index and which variables are better left as possible moderators.

Male gender has been used as a risk factor in a handful of the studies reviewed. Although this can be a useful indicator for some types of outcomes (i.e., externalizing disorders), being female is a greater risk for other outcomes (i.e., internalizing disorders). In a similar vein, minority racial/ethnic status presents the same difficulty. Whites seem to suffer more from added stresses (Deater-Deckard et al., 1998; Gerard & Buehler, 2004b), yet non-White minority status covaries with SES and non-Whites likely experience different forms of personal and institutional racism (Spencer, 2005). Which group is at risk then?

Furthermore, if the additive assumption of cumulative risk models were correct then all studies would find evidence of equifinality similar to the work of Sameroff and Deater-Deckard (Deater-Deckard et al., 1998; Sameroff et al., 1987). However, some research actually suggests the contrary. In studying the effect of multiple risk factors on the social competence of preschoolers, Corapci's (2008) cumulative risk model indicates that the number and type of risk factors seem to matter. When the CR index was composed of eight variables, CR did not significantly predict preschooler social competence. However, when two additional temperament variables were included (impulsivity and inhibition) the CR index significantly predicted teacher ratings of social competence.

This work causes one to question the functional form of risk. If the number and type of risk factors in a model differentially impacts how risk functions, then a non-additive model may be necessary. As displayed in Figure 2, the question of how risk functions is just as important as how risk should be measured. Because the cumulative risk model falls under the additive model branch of Figure 1, a linear function between risk level and outcome is assumed (Figure 2a). However, it is entirely possible that variables within the risk index interact with one another (Figures 2b and 2c). Current cumulative risk models cannot test for interactions between risk variables.

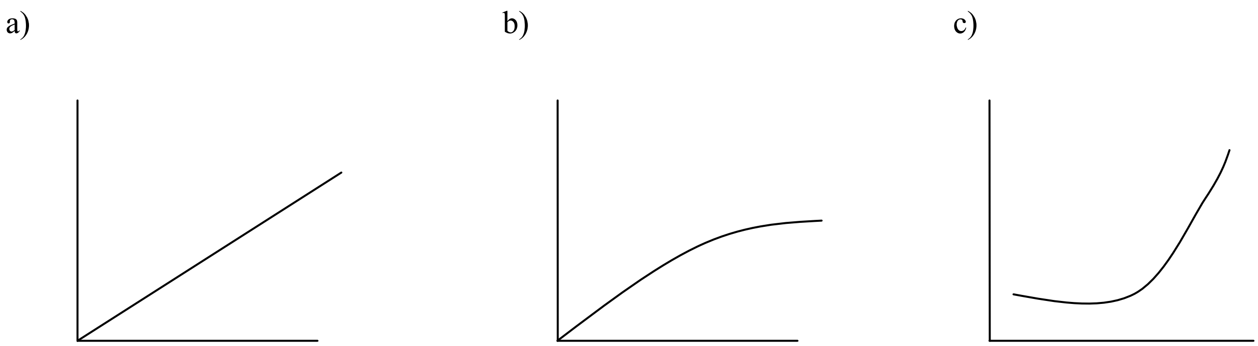

Figure 2. Functional form of cumulative risk, a) additive, b) non-additive, threshold , c) non-additive mass accumulation.

Interestingly, some CR studies within child development, including Rutter's foundational work, indicate that multiple risks take on a non-linear form (Pollard et al., 1999; Rutter, 1979; Werner & Smith, 1977). Though the majority of CR studies do not statistically test for curvilinear effects, the results of those that do are mixed. While several studies have indeed supported a linear risk function (Appleyard, Egeland, van Dulmen, & Sroufe, 2005; Gassman-Pines & Yoshikawa, 2006; Gerard & Buehler, 2004a), other work has reported significant effects for quadratic CR terms (Krishnakumar & Black, 2002; Morales & Guerra, 2006). These latter results undermine the additive assumption implicit to CR models.

As a possible way around this issue, Ackerman and colleagues (1999), suggest that family process variables should be treated as moderators of risk rather than as contextual risk variables themselves. Ackerman used distal risk factors - negative life events, changes in family residence, psychiatric episodes of parents, family being on welfare - in his study of children's problem behaviors. Other researchers (Evans, Kim, Ting, Tesher, & Shannis, 2007; Jones et al., 2002; Luthar, 1993) have also supported the use of indirect effects models that consider how distal cumulative risks operate through more proximal processes. Nevertheless, such models still assume that risk factors themselves are independent of each other.

New Evidence for Interaction Effects in Cumulative Risk Models

Due to their dichotomization approach cumulative risk models have the distinct advantages of being able to model multiple risk factors with small samples and avoiding problems with multi-collinearity. However, the traditional lump sum CR approach is based on an implicit assumption that risks are additive. This is a major drawback to CR and is in need of further exploration. A number of recent studies have challenged this assumption and presented evidence to the contrary.

Pungello and colleagues (1996) examined the long-term effects of multiple risk factors on math and reading achievement in elementary and middle school children. A three-variable cumulative risk index (family income, ethnicity, life events) significantly predicted both math and reading achievement.

However, when the researchers created a multiplicative model with math achievement as the dependent variable, a significant interaction between family income and ethnicity was detected. The difference in math scores of European American children in low income homes and those not living in low income homes was larger than the difference in math scores of African American children living in a low income home versus those not living in a low income home. Additionally, researchers detected an interaction between income and grade (time). Scores of children not living in a low income home increased over time whereas scores of children in a low income home decreased with time. Using the multiplicative model with reading achievement as the dependent variable, the researchers detected a significant interaction between gender and grade (time). While reading scores for girls increased over time, scores for boys remained relatively stable.

This work suggests that different predictors are important for reading and math achievement. Specifically, results of the multiplicative model imply that income-related differences in reading achievement emerge early and remain relatively stable whereas income-related differences in math achievement among children emerge later and increase over time. While the additive dichotomized model was a significant predictor of both math and reading achievement, the multiplicative model provided greater insight into the intricate workings of these three risk variables. The interaction findings challenge the additive assumption of the CR model. At the same time, however, the additive CR results suggest that the co-occurrence of all three risks was impactful.

Atzaba-Poria and colleagues (Atzaba-Poria, Pike, & Deater-Deckard, 2004) found that "microsystem-level" CR (i.e., parental use of discipline, parent-child relationship) was most predictive of externalizing problems in children while "exosystem-level" CR (i.e., family SES, parental marital relationship) was the most significant predictor of internalizing problems. A handful of other studies have examined whether risk experienced in more than one ecological context is more damaging than risk experienced in 0 or 1 context (Gerard & Buehler, 2004a; Morales & Guerra, 2006; Simmons, Burgeson, Carlton-Ford, & Blyth, 1987; Thornberry et al., 1997).

In a 2007 article, Evans and colleagues reported an interaction effect between their nine variable cumulative risk index and a maternal responsiveness measure. The researchers found that children's allostatic load increased when cumulative risk increased, but only for those children experiencing low maternal responsiveness.

Brennan and colleagues (Brennan, Bor, Najman, & Williams, 2003) categorized risk according to biological and social components to predict three types of aggression patterns in children (early onset and persistent, adolescent onset, and non-aggressive). The social CR category differentiated groups to some degree while the biological CR category did not significantly predict any of the patterns of aggression. Most noteworthy, the authors found two significant interaction effects between social CR and biological CR. The interaction term differentiated between early onset and non-aggressive youth and between early onset and adolescent onset aggression.

In a similar analysis, researchers examined the impact of cumulative violence exposure across three settings – the home, neighborhood, and school. Three CR indices were created and used to predict anxiety, depression, aggressive fantasies, aggressive behaviors, and delinquency. Home violence CR x neighborhood violence CR significantly predicted anxiety and depression; the negative impact of violence within the home was accentuated in low violence neighborhoods. Additionally, neighborhood violence CR x school violence CR significantly predicted aggressive fantasies and delinquency; the negative impact of school violence was accentuated in low violence neighborhoods (Mrug, Loosier, & Windle, 2008).

Whipple, Evans, Barry, & Maxwell (2010) found that school-wide academic performance was predicted by the interaction of neighborhood-level and school-level risk factors. At the same level of school risk, academic performance varied based on neighborhood risk. Specifically, the adverse effects of school CR on school-wide academic achievement were exacerbated in moderate risk neighborhoods.

These studies provide a working prototype for examining interaction effects between risk variables, even in cumulative risk models. Such methodology extends CR research by retaining the benefits of traditional models while also addressing drawbacks of the technique. For one, if risk domains are not examined, interaction effects cannot be detected in a CR model. Moreover, interaction effects provide meaningfully different information than a main effect of total CR. Thus, by allowing for the occurrence of interaction effects, a domains approach can better specify *how* risks operate. In this paper I use this prototype to examine how different domains of cumulative risk interact. In doing so, I address the concern that CR models often lump distal risks (i.e., socio-demographic) and proximal risks (i.e., parenting) in the same model (Deater-Deckard et al., 1998; Greenberg et al., 2001). I resolve this limitation by borrowing from Bronfenbrenner's Ecological Systems Theory (1979), to which I turn now.

The Ecological Domains Approach

Bronfenbrenner's Ecological Systems Theory views human development as an evolving interaction between the person and the environment (Bronfenbrenner, 1979). The ecological environment is conceptualized as a nested structure composed of several interacting systems (see Figure 3). The innermost level of this nest is the developing person's immediate setting, oftentimes the home, classroom, or even the laboratory in the case of experimental research. Topologically, several concentric circles surround this inner level; each circle is contained in the next. As its name suggests, Ecological Systems Theory improved upon previous methods of understanding human development by extending focus beyond a singular setting. Thus, a primary principle of this theory is its emphasis on the relations between multiple settings.

A number of terms are used to describe the settings and interconnections between settings central to Bronfenbrenner's model. I briefly review these terms now. To begin, the *microsystem* is the immediate environment in which the child is embedded. Topologically, this is the circle closest to the child. The most common microsystem analyzed is the home, though there are a number of other places in which the child can be directly located - daycare, school, the peer group, etc. To understand a microsystem's influence on a child both the objective features of that environment along with the ways in which the developing person subjectively experiences that environment are important. Thus, the individual's connections with other persons in that setting and his/her role in the environment are critical elements to understanding the microsystem of interest. Next, the *mesosystem* describes the interaction between two settings (microsystems) in which the person is actively embedded. For example, a child's reading ability cannot be understood merely as a result of school or teacher quality. That child is simultaneously, and also historically, also engaged in the home setting. Thus, the home environment and ties between the home and school must be taken into consideration to gain a fuller understanding of reading ability. *Exosystems* refer to those environments external to the developing person. In the case of children, exosystem examples include parental workplace, parental social networks, and community influences. An exosystem affects the child indirectly through its influence on family processes.

Microsystems, mesoystems, and exosystems are the crux of my approach to understanding domains of risk. Nevertheless, it is worth noting two other types of systems inherent to the ecological systems model. The *macrosystem* refers the larger socio-cultural context. The macrosystem tends to account for consistencies in the form and content of lower-order systems (micro-, meso-, exo-). These consistencies tend to exist due to cultural norms and overarching ideologies. Lastly, *chronosystems* make it possible to examine how change (or continuity) over time affects the developing person in his/her environment. Simple chronosystems focus on life transitions, be them normative (i.e., school transition), or nonnormative (i.e., divorce, death in the family). While these two systems are not as crucial to the domain-specific risk model I hypothesize here, they are nevertheless significant to understanding Bronfenbrenner's Ecological Systems Theory (Bronfenbrenner, 1986).

To summarize, Urie Bronfenbrenner revolutionized human development research by discerning that the interactions between settings are as important to development as the interactions between people and conditions within settings. This assertion is key to the domain-specific cumulative risk model I propose, since I attempt to understand cumulative risk as an interaction between multiple environments to which the child is exposed.

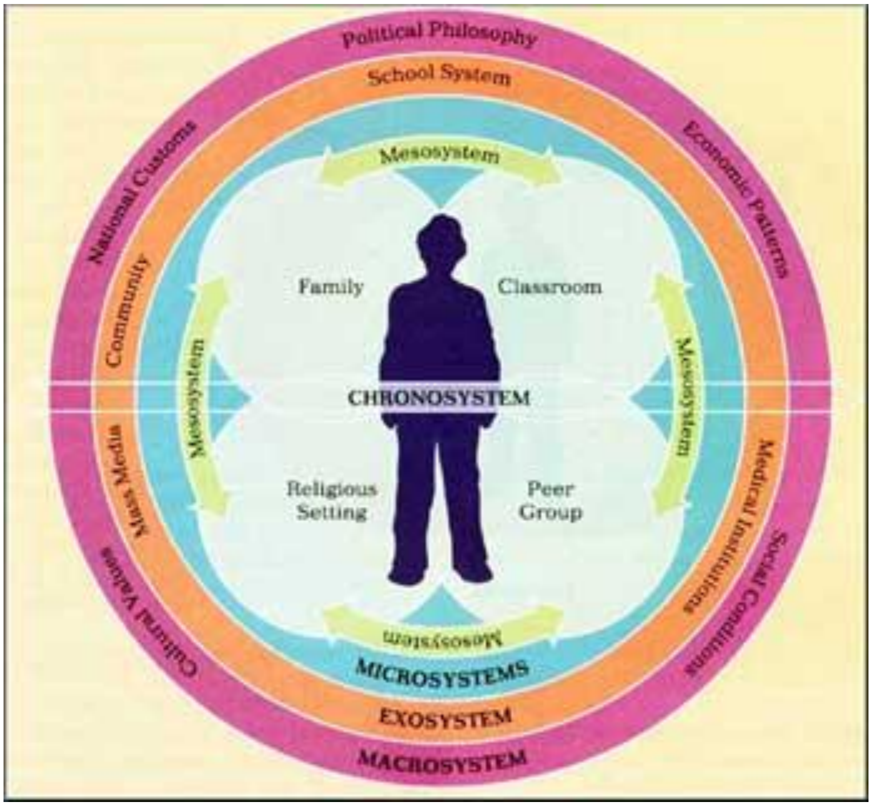

Figure 3. The Ecological Systems Model of Human Development.

The Ecological Cumulative Risk Model

At this point in time several things should be clear: 1- risk research is inherently complex, 2 - typical risk models require large sample sizes to effectively model multiple, simultaneously occurring variables, 3- cumulative risk methodology addresses some of these statistical limitations but a) often fails to consider how both proximity of risk to the child and the setting of that risk influence developmental outcomes, b) assumes risk is additive and therefore risks act independently of each other. With all of this in mind, the central goal of this paper is to examine a multi domain cumulative risk model. Specifically, I intend to examine cumulative risk within environmental domains that are of varying proxim ity to the child. A large-scale national dataset, the NICHD Study of Early Child Care and Youth Development, will be used to assess the utility of the Ecological Cumulative Risk Model in predicting developmental outcomes of 4^{th} grade children. The variety of methods and observers used in the study allows me to model multiple risk factors, domains, and outcomes to determine the utility of this methodology. If my hypotheses are supported, such an ecological cumulative risk model can then be applied to smaller, less resourceful datasets.

Figure 4 shows a visual conceptualization of this model. The overall image is presented like a structural equation model, in which ovals represent latent constructs (domains) that are essentially created from the indicator variables (risks). There are five risk domains pictured: demographics, home environment, parent behaviors, school, and neighborhood. A cumulative risk index will be constructed for each domain presented. For example, since there are five proposed demographic variables, a child could score between 0 and 5 on this cumulative risk domain.

With reference to Bronfenbrenner's Ecological Model, demographic risk is the most distal of the domains pictured in Figure 4. Certainly demographic-level risk can affect the individual child. However, the process through which risk in a macrosystem impacts an individual is not the same as the means by which risk in a microsystem impacts that same person. According to Bronfenbrenner, macrosystem-level risks essentially feed through microsystems, environments in which a person physically resides. Take the current economic recession for example. The recession itself is not directly affecting individual children's developmental outcomes. However, because unemployment is high many parents may be out of work. As a result, family incomes suffer. When income declines families may need to move to less optimal neighborhoods with fewer high quality schools. Additionally, parents may suffer from depression which can influence their parenting abilities. Conditions in each of these microsystem contexts can thereby influence child development. By extension, Bronfenbrenner's Ecological Systems Model implies some form of mediation between levels. For example, family demographics at least partially mediate the impact of national economic conditions on the individual child's well-being.

In order to understand the impact of ecological risk on child development I chose to examine four broad developmental outcomes– cognitive/academic performance, internalizing behaviors, externalizing behaviors, and social skills (Figure 5). The risks and outcomes included in this model are both theoretically and empirically supported, as reviewed now.

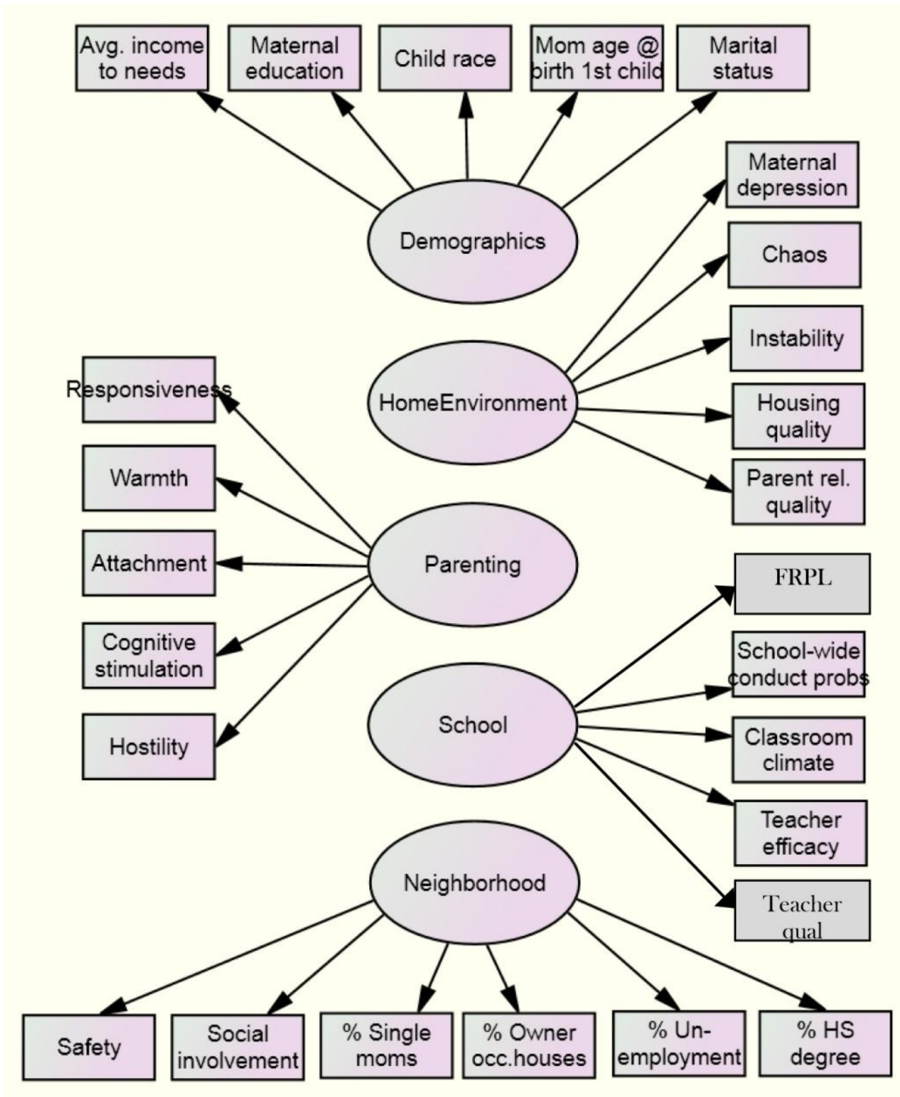

Figure 4. Risk variables and hypothesized domains of an ecological CR model.

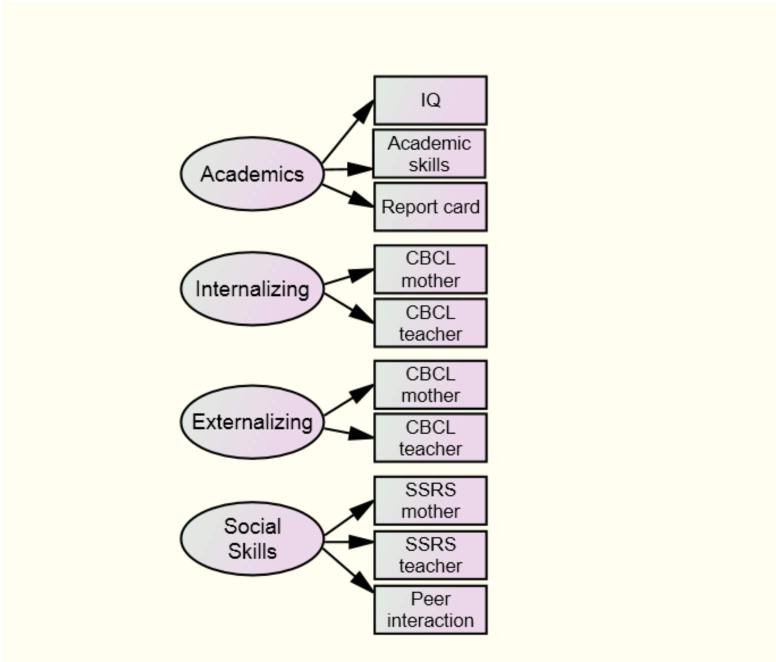

Figure 5. Four outcome domains with their respective variables.

Demographic Risk

Five risk factors have been identified as potential components of the demographic risk domain: family income, parental education, parental marital status, mother's age at birth of first child, and child race. As Huston and Bentley (2010) point out these demographic variables are not only highly inter-correlated, but they exert influence over each other. Thus the rationale for including them as indicators for demographic risk is well-founded.

Both naturalistic and experimental research have found evidence that family income positively influences children's school achievement and socio-emotional development (Chase-Lansdale et al., 2003; Duncan, Morris, & Rodrigues, 2011; Kalil & Dunifon, 2007). Additionally, poverty in early and middle childhood predicts children's later behavior problems (Votruba-Drzal, 2006).

Mercy & Steelman (1982) reported that each of their SES indicators (family income, maternal education, and paternal education) predicted intellectual attainment in the Health

Examination Survey, but that maternal education acted as the strongest predictor. Parental education has also been linked to children's language performance (Magnuson, Sexton, Davis-Kean, & Huston, 2009).

Children with stable behavioral problems are more likely to have younger parents and come from one parent households (McGee, Williams, & Silva, 1984). Mother's age at birth of first child is predictive of children's reading recognition ability and IQ (Baldwin & Cain, 1980; Dubow & Luster, 1990; Furstenberg, 1976), along with some evidence for adolescent emotional adjustment (Baldwin & Cain, 1980). Children from one parent households are more likely to experience academic difficulties and higher levels of social, psychological, and behavioral problems than peers from two-parent families (Amato, 1994; Dawson, 1991; McLanahan, 1997; Mulkey, Crain, & Harrington, 1992). Single parents are at increased risk for developing depression, which compromises effective parenting practices (Carlson & Corcoran, 2001; McLanahan & Adams, 1987).

With regard to race, African American and Hispanic children enter school behind their non-Hispanic White counterparts in measures of cognitive development, school readiness, and achievement (Huston & Bentley, 2010; Lee & Burkham, 2002; Planty et al., 2009).

Home Environment Risk

Five risk factors have been identified as potential components of the home environment risk domain: parental mental health status, chaotic/unpredictable home environment, instability, housing quality, and parental relationship quality.

Parental psychopathology is related to children's conduct problems, cognitive competence, and socioemotional adjustment (Cummings & Davies, 1994; Eamon, 2001; McGee et al., 1984). Parental depression in particular has been shown to impair children's socioemotional functioning through inconsistent and uninvolved parenting (Conger, Conger, Elder, Lorenz, Simons, & Whitbeck, 1993; Cummings & Davies, 1994).

Chaotic or unpredictable home environments affect socioemotional development, presumably by undermining self regulation processes (Bronfenbrenner & Evans, 2000; Evans, Gonnella, Marcynyszyn, Gentile, & Salpekar, 2005; Fiese & Kline, 1993; Repetti, Taylor, & Seeman, 2002; Wachs, 2000). In addition, the experience of stressful life events predicts a range of adjustment problems, including social withdrawal (Rutter, 1983), school adjustment problems (Pryor-Brown & Cohen, 1989), psychological distress (Compas, Howell, Phares, Williams, & Giunta, 1989; Dubois, Felner, Brand, Adan, & Evans, 1992; Wagner, Compas, & Howell, 1988; Windle & Windle, 1996), self-reported delinquency (Tolan, 1988; Vaux & Ruggerio; 1983; Windle & Windle, 1996), and lower GPA (Windle & Windle, 1996).

Interadult conflict causes distress in children and compromises feelings of security (Davies & Cummings, 1994). There is a wide range of evidence that exposure to conflict within the home environment is associated with increased risk for externalizing problems and internalizing problems as well as impaired cognitive and social competence (Buehler et al. 1998; Emery, 1982, 1988; Forehand, Neighbors, Devine, & Armistead, 1994; Repetti et al., 2002).

Substandard housing quality directly impacts physical health by contributing to childhood injuries (Leventhal & Newman, 2010; Matte & Jacobs, 2000; Satterthwaite et al., 1996). Furthermore it has been found to impair socioemotional functioning (Gifford & Lacombe, 2006) and contribute to psychological distress (Evans, Wells, Chan, & Saltzman, 2000). Similarly, the degree to which a child’s home environment is stimulating is a consistent predictor of cognitive performance (Bradley, Corwyn, Burchinal, McAdoo, & Garcia Coll, 2001) and behavior problems (Carlson & Corcoran, 2001). Parent-to-child speech (Hart & Risley, 1995; Hoff, Laursen, & Tardif, 2002) and exposure to print media (Neuman & Roskos, 1993) influence cognitive development.

Parent Behavior Risk

Five potential risk factors have been identified for the parent behavior risk domain: attachment, warmth, responsiveness, hostility, and cognitive stimulation.

Children with insecure attachments to their primary caregivers are more likely to exhibit externalizing and problem behavior (Greenberg, Speltz, DeKlyen, & Endriga, 1991; Shaw & Vondra, 1995; Speltz, Greenberg, & DeKlyen, 1990). In addition, securely attached children show better school adjustment as indicated by teacher reports of academic, social, emotional and behavioral adjustment (Granot & Mayseless, 2001).

The impact of parental responsiveness on positive child outcomes cannot be overstated. Maternal responsiveness is associated with the growth of cognitive, and more specifically, linguistic, competence (Bloom, 1993; Bornstein & Tamis-LeMonda, 1989; Bornstein, Tamis-LeMonda, Hahn, & Haynes, 2008) as well as IQ and social competence (Ainsworth & Bell, 1974).

Maternal warmth is linked to better regulation of positive affect (Davidov & Grusec, 2006), child social skills (Steelman, Assel, Swank, Smith, & Landry, 2002), teacher ratings of academic motivation (Radin, 1971), GPA and school achievement (Estrada, Arsenio, Hess, & Holloway, 1987; Kim & Rohner, 2002), and among boys, to greater peer acceptance (Davidov & Grusec, 2006). There is some evidence that sensitive caregiving socializes children’s achievement motivation (Hokoda & Fincham, 1995).

Hostile parenting predicts less socially competent behavior in children (Baldwin, 1955; Baumrind, 1967; Pettit, Dodge, & Brown, 1988; Putallaz, 1987; Stocker & Youngblade, 1999). Exposure to high levels of parent-child hostility puts children at risk for developing internalizing and externalizing disorders (Gordis, Margolin, & John, 2001; Low & Stocker, 2005). Moreover, socially competent children are less likely to have mothers who endorse aggression (Pettit et al., 1988).

As mentioned previously, the degree to which a child's home environment is stimulating is a consistent predictor of cognitive performance (Bradley, Corwyn, Burchinal, McAdoo, & Garcia Coll, 2001) and behavior problems (Carlson & Corcoran, 2001). Furthermore, parental scaffolding has been linked to children's word learning (Blewitt, Rump, Shealy, & Cook, 2009), subsequent self-regulatory competence in children (Neitzel & Stright, 2003), and reasoning skills in children (Stright, Herr, & Neitzel, 2009).

School Risk

Young children spend a significant portion of their lives in school; as such the school environment is a worthwhile domain for the investigation of risk. Although the school risk literature can at times be contradictory, researchers tend to agree that specific measures of school quality affect student achievement and test scores (Burtless, 1996; Card & Krueger, 1996; Hanushek, 2002). Thus, five possible risk factors have been identified for this domain: teacher qualifications, percentage of school population receiving free or reduced price lunch, teacher efficacy, classroom climate, and school-wide conduct problems.

The degree of available resources in a school is positively related to student achievement (Hedges & Greenwald, 1996). Per pupil expenditures have been linked to better student performance through reduced class size (Wenglinsky, 1997) and better-educated teachers (Elliott, 1998).

High quality teachers matter, so much so that having three years of good teachers in a row can overcome the average achievement deficit between low-income students and their peers

(Hanushek, 2002). Qualified teachers are capable of eliciting significant gains from students of all ethnicities and income levels (Rivers & Sanders, 2002). Measures of teacher preparation and certification are correlated with student achievement in both math and reading (Darling-Hammond, 2000; Rivkin, Haushek, & Kain, 2005). In fact teacher quality explains at least 7% of the variance in student achievement, with the true percentage likely being much larger (Hanushek, Kain, & Rivkin, 1998).

The social composition of a school predicts the performance and behavior of its students (Caldas & Bankston, 1997; Huston & Bentley, 2010). In particular, the percentage of low income children predicts the rate with which reading skills grow over the elementary school years (Aikens & Barbarin, 2008).

The mean achievement of one's peers is positively correlated with a student's school performance (Ryan, 2000). Furthermore, the number of children in a school with reading deficits impacts individual children's learning rates in reading (Aikens & Barbarin, 2008).

Neighborhood Risk

The range of child outcomes associated with neighborhood disadvantage is broad, ranging from infant mortality, teenage childbearing, high school dropout, child maltreatment, and adolescent delinquency (Brooks-Gunn, Duncan, & Aber, 1997; Sampson, Morenoff, & Gannon-Rowley, 2002). Six possible variables have been identified for the neighborhood risk domain: unemployment rate, percentage of adults with a high school degree, percentage of single women with children younger than 18 years-old, percentage of owner-occupied houses, safety, and social involvement.

In a comprehensive review Leventhal & Brooks-Gunn (2000) found that the most consistent finding was the influence of affluent neighbors on child IQ, verbal ability, and academic achievement. Social involvement or cohesion has been used to explain the association between neighborhood economic status and child outcomes (Cook, Shagle, & Degirmencioglu, 1997). Disadvantaged neighborhoods often have fewer social ties, which leads to the breakdown of conventional norms and behaviors (Coleman, 1988; Ross & Jang, 2000; Sampson & Groves, 1989). However, if parents in poor or dangerous neighborhoods receive adequate social support, parental stress can be reduced; in turn, the negative effects of parental stress on child outcomes are reduced (Conger, Ge, Elder, Lorenz, & Simons, 1994; Elder, Eccles, Ardelt, & Lord, 1995; McLoyd, 1990). In fact, Coleman and colleagues have reported that social relationships within the community promote competence in children (Coleman, 1994; Coleman & Hoffer, 1987). Furthermore, neighborhood social integration is associated with prosocial behaviors and positive developmental outcomes in adolescents (Steinerg, Darling, & Fletcher, 1995).

Goals of the Current Study

The Ecological Cumulative Risk Model is intended to shed light upon how the number of risks experienced across multiple domains can affect developmental outcomes in elementary-aged children. Unlike traditional cumulative risk models I do not merely collapse across type or proximity of risk to look at a total risk score; instead I will tally the number of risks experienced within specific life domains. It is anticipated that this type of measurement model will give insight into the possible interactions between different types of proximal and distal risk domains. For example, if a household has several demographic risk factors (i.e., income below the poverty line, primary caregiver who has not completed high school, and single parenthood), it is highly likely that when multiple risks are experienced in another domain (i.e., the school environment), that a child will be at jeopardy for poor developmental outcomes compared to the child who experiences high risk in only one domain. The reason for this interactive effect can be understood in terms of Simmons et al.'s (1987) "arenas of comfort" perspective. If change occurs too suddenly or too early given a child's limited cognitive and emotional development, *or* if change occurs in too many areas at once, the individual will experience discomfort. Stressors in one area of life (i.e., single parent) should be easier to deal with if an individual has other "arenas of comfort" (i.e., social support outside of family). Consequently, when an individual is assaulted with multiple stresses at once he/she experiences diminished comfort and has difficulty coping. Indeed, empirical work by Simmons and colleagues (1987) confirmed that children confronted with several simultaneous stressors suffered declines in both GPA and self-esteem.

Using the NICHD Study of Early Childhood and Youth Development, my goal is to create a cumulative risk index for each of the domains depicted in Figure 4. Based on these indices I will analyze data to answer the following questions:

(1) How well do the total CR index ("lump sum") and the domain specific CR indices predict variance across several outcomes – academic, internalizing behaviors, externalizing behaviors, and socio-emotional skills?

(a) Does the total CR index add any predictive power over and above that of the domain-specific CR indices?

(2) Do risk domains statistically interact to impact outcome measures? To examine this question, interaction effects of distal and proximal risk categories will be tested:

(a) How do demographic CR and home environment CR interact to affect each outcome?

(b) How do demographic CR and parenting CR interact to affect each outcome?

(c) How do home environment CR and neighborhood CR interact to affect each outcome?

(d) How do home environment CR and school CR interact to affect academic outcomes in particular?

(e) Based on results from 2a, b, c, and d any potential three-way interaction effects will also be tested.

(3) Which model, total risk or domain-specific risk, is best supported using structural equation modeling (SEM)? SEM capitalizes on the continuous nature of data and allows for the creation of latent constructs. Therefore, this analysis does not provide any additional support for cumulative risk per se. However, if domain-specific risks fit the data better than a lump sum approach then the ecological part of the proposed model would garner further support.

(4) Does mediation through domains of risk occur? In order to determine a potential path of risk, a structural model examining distal (demographics) and proximal (parenting) domains will be estimated.

Hypotheses

I hypothesize that both the traditional (total/lump sum) CR model and the ecological domains CR model will explain a significant proportion of variance in each of the outcome measures. However, the domain specific CR model will give much-needed insight into how each risk domain independently contributes to outcomes when other domains are held constant. With regard to question 1a, I do not anticipate that total CR will add additional predictive power to the models when domain specific CR is controlled for.

Next, I hypothesize that as a more distal risk domain, demographic CR will interact with both parenting CR and home environment CR. Increasingly poorer outcomes will occur when socio-demographic risk is high, but only for those children experiencing high risk in the other domains. In sum, parenting behaviors and the home environment are anticipated to moderate the relationship between demographic cumulative risk and all outcome domains.

Because this sample involves 4th grade children it is possible to look at the influence of both school and neighborhood risk factors as well. I predict that high risk status within these domains will put children who already face multiple risks within the home environment at a significant disadvantage academically, socially, and behaviorally. In other words, when risk in the home environment is held constant, those experiencing higher risk in the school or neighborhood domains will face bleaker outcomes.

With regard to the structural equation analyses, I hypothesize that a domain specific measurement model will prove to fit the data better than a lump sum model. Furthermore, I predict that distal risk operates through more proximal domains, providing evidence of domain mediation.

METHODS

Theoretical Rationale for Choosing Risk Factors and Domains of Risk

I based the risk variables in my model on two considerations. The first consideration was purely theoretical. Based on past research, I generated a list of variables that pose risks for children across multiple developmental domains. Next I consulted various secondary datasets to determine if they would support the modeling of these most important risk factors (i.e., maternal level of education, maternal mental health status, instability within the home, parental responsiveness). The NICHD Study of Early Child Care and Youth Development (SECCYD) was chosen particularly for its ability to support a number of risk variables and outcome constructs. The final step in the process was to comb through questionnaires and measures used in the NICHD study for other potential risk variables of interest. Although many variables suffer from potential measurement problems (i.e., minimal questions that tap into the variable of interest), each risk variable chosen for this study is theoretically based.

Demographics, the home environment, and parent behaviors are the most commonly assessed types of risks in psychological CR research, as these are particularly relevant domains for very young children. School and neighborhood were chosen as two additional risk domains due to their near universality for elementary-aged children.

The Dataset

The NICHD Study of Early Child Care and Youth Development was initiated by the National Institute of Child Health and Human Development (https://secc.rti.org/). It is the most comprehensive study on child care and child development to date. Data collection began in 1991 across 10 U.S. locations. At that point in time 1364 children were enrolled in the study. Approximately 1077 of these children have been followed until present day. The independent variable data used for this analysis will come primarily from the 3rd grade assessment, with outcomes being measured at 4th grade. It is important to note that similar outcome measures were collected during the 3rd grade assessments so that prior levels of each outcome can be statistically controlled. These time points were chosen because it is still relatively early in the child's life, yet the child is of school-age. Furthermore, unlike other earlier assessment time points, the 3rd grade assessment contains a number of school and neighborhood risk variables and the 4th grade assessment incorporates a number of socio-emotional measures.

Measures

Demographics

Income-to-Needs. Income information was collected from study families at nearly every visit since birth. Using this information along with family demographics, researchers with the Study of Early Child Care calculated income-to-needs ratios throughout the study. Income-to-needs is a commonly used demographic variable that takes family size into account when calculating income. In this case income is defined as any sources of income including government aid. The ratio is determined by comparing the family's total income to an established poverty threshold for a family with that number of full-time adult and child residents within the household. Thus, the ratio is defined as total family income/federal poverty threshold for a family with the same household composition. A value of 1.0 represents a family that is at the poverty line. An income-to-needs ratio of greater than 1.0 represents a family above the poverty line while a ratio of less than 1.0 represents poverty. NICHD researchers used the Poverty Thresholds from the U.S. Census Bureau, Current Population Survey to determine these thresholds (NICHD SECCYD, CCDR 204, 1998).

Income-to-needs variables at 1 month, 6 months, 15 months, 24 months, 36 months, 54 months, kindergarten, 1st grade, and third grade were extracted for the purposes of this study. Because family income can fluctuate greatly, the average income-to-needs ratio over these nine time-points was calculated for each study child.

Maternal Education. Mothers reported their highest level of education when the study began and again at the 36-month assessment. The more recent maternal education variable was used unless it was unavailable for a particular case.

Maternal Age at Birth of First Child. Mother's age when first child was born was calculated through a series of variables. If the target child was not reported as the first-born, household demographic data were consulted to determine the age of the oldest child. This value was subtracted from the mother's reported age at the month 1 assessment.

Maternal Marital Status. Marital status was determined through two interview questions during the third grade assessment. The first question asked mothers to report marital status while the second question asked if the biological father or a stepfather lived in the home.

Child Race. Mothers reported their child's race and ethnicity at the month 1 assessment.

Home Environment

Maternal Depression. Caregiver mental health was assessed at each visit with a modified version of the Center for Epidemiological Studies Depression Scale (CES-D, Radloff, 1977). The survey is scored on a 4-point Likert scale (0 = less than once a week; 3 = 5-7 days a week). The scale has good internal consistency, α =.87-91. Possible scores range from 0 to 60, with higher values indicative of depressive symptoms.

Instability. Instability was calculated by tallying the number of residential moves, changes in household resident make-up, and school or daycare provider changes throughout the child's life. The primary caregiver regularly reported on these changes during routine surveys and phone updates. Instability is defined here as the total number of these changes experienced by the child from birth through third grade.

Chaos. The Confusion, Hubbub and Disorder Scale (CHAOS, Matheny, Wachs, Ludwig, & Phillips, 1995), administered in the 3rd grade wave of data collection, was used to measure daily routines within the home. Parents responded either 'true' or 'false' to 15 questions that inquire about family routine and level of predictability within the home environment. The total number of yes responses (reflecting chaos) was tallied for an overall score. This scale has good test-retest reliability, α = .74.

Housing Quality. Housing quality was calculated using the Middle Childhood Home Observation for Measurement of the Environment Inventory (H.O.M.E., Bradley, Caldwell, & Rock, 1988; Caldwell & Bradley, 1984). The Physical Environment subscale of the H.O.M.E. is composed of 8 questions. Observers report on whether the home shows evidence of physical hazards, safety, cleanliness, and crowding. This items on the scale have modest reliability, α = .69 (NICHD SECCYD, CCDR 380, 2002).

In addition, two measures were used to evaluate the degree of stimulating materials within the home. The Learning Materials subscale of the Middle Childhood H.O.M.E. is composed of 8 interview questions that assess whether the parent encourages the learning of age-relevant information. For example, one question on the scale requires observers to determine if the child has access to 10 appropriate books. The items used to create the subscale have low internal reliability, $\alpha = .41$ (NICHD SECCYD, CCDR 380, 2002). As a result, select questions from the Home Literacy Environment Questionnaire, a newly developed measure, were used to supplement this subscale of the H.O.M.E. The Literacy Questionnaire asks questions about the use of television, computers, and frequency of reading in the home environment. The scale is reliable, $\alpha = .75$. *Z* scores for each subscale were calculated and summed to create an overall index of housing quality.

Parent-Partner Relationship. The Love and Relationships scale of the NICHD study is a 6 item subcomponent of the Personal Assessment of Intimacy in Relationships scale (PAIR, Shaefer & Olson, 1981). This scale was used to assess the degree of partner intimacy and conflict. Possible responses range from 1 to 5 with higher responses indicative of better quality relationships. The scale has good reliability, $\alpha = .70$

Parent Behaviors

Attachment Security. Two measures were used to assess attachment security. The affective mutuality/felt security scale is an observational scale used during a semi-structured problem-solving task with mother and child and father and child at the 3rd grade assessment. The scale measures the degree to which the child feels secure with the parent. Open and free communication is a central component of this measure. Those dyads scoring low on this scale show a non-reciprocal or stifled interaction. The scale ranges from 1 (very low) to 7 (very high).

Scores from the Child-Parent Relationship Scale (Pianta, 1992, 1994) were used as an additional measure of attachment. This questionnaire, designed to assess the child's attachment behaviors toward the parent, was administered to parents during the 3rd grade wave of data collection. It uses a 5-point Likert response scale and has 30 items total. Three subscales compose the scale: conflict with child, closeness with child, and total positive relationship with child. Reliability coefficients for the subscales range from .65 to .87. *Z* scores for each scale were calculated and summed to create a standardized score of attachment.

During the same semi-structured problem-solving task mentioned above, NICHD observers also coded for parental hostility, stimulation of cognitive development, quality of assistance, and supportive presence.

Parental Hostility. Hostility scores indicate the degree to which the parent expresses anger, discounting, or rejection toward the child. A parent scoring high on this scale overtly rejects the child and blames him/her for mistakes. The scale ranges from 1 (very low) to 7 (very high).

Stimulation of Cognitive Development. The scaffolding/stimulation of cognitive development scale measures the parent's effortful teaching and the degree to which she fosters the child's mental development. Highly stimulating parents explain concepts, use analogies, use context to teach, and encourage problem-solving. Parents scoring low in stimulation make no attempt to teach the child. The scale ranges from 1 (very low) to 7 (very high).

Parental Warmth. The parent supportive presence scale measures the degree to which a parent expresses positive regard and emotional support to the child during the semi-structured interaction task. The parent who scores low on this measure is unavailable, aloof, or even hostile. The scale ranges from 1 (very low) to 7 (very high).

Additionally, scores from the "My Family Questionnaire" (Relatedness Questionnaire, Lynch & Cicchetti, 1997; Toth & Cicchetti, 1996), a child-completed survey were used to supplement the parental warmth variable. This questionnaire assesses the child's feelings toward the primary caregiver. The items used to create these scores have moderate internal reliability, Cronbach's alpha = 0.78 - 0.85.

Z scores of these two measures were calculated and summed to create a standardized warmth score.

Parental Responsiveness. Parental responsiveness scores were obtained from the Responsivity and Acceptance scales of the Middle Childhood H.O.M.E (Bradley et al., 1988; Caldwell & Bradley, 1984) during the 3rd grade assessment. The 59-item H.O.M.E. scale uses a combination of direct observation and semi-structured interviews with the mother; "yes" and "no" are the possible responses. The 10 items used to create the Responsivity scale, as well as the 8 items used to create the Acceptance scale showed low internal reliability, $\alpha = .44$ and $\alpha = .38$, respectively (NICHD SECCYD, CCDR 380, 2002)

Neighborhood

Safety and Social Involvement. Parents and their children completed neighborhood questionnaires when children were in 3rd grade. For children, this questionnaire is a 16-item revised version of the *Self Care Checklist* (Shumow, Vandell, & Posner, 1998; Vandell & Posner, 1995). Responses range from 1 (not at all true) to 5 (really true). The questionnaire is administered in an interview-type format; children answer by pointing to response cards. The scale taps into two dimensions – perceived neighborhood safety and emotional readiness. For the purposes of this study the neighborhood safety scale was used. The safety scale is composed of 7 items and has good reliability, $\alpha = 76$ (NICHD SECCYD, CCDR 409, 2002).

The Neighborhood Satisfaction and Involvement scale (Greenberg, Lengua, Coie, Pinderhughes, & Conduct Problems Prevention Research Group, 1999) was administered to parents to assess perceptions of neighborhood resources, cohesion, support, and safety. It is a 16-item measure with three scales: safety, social involvement, and public services. The safety and social involvement scales are reliable, α = .70-.74.

The parent and child versions of the safety subscale were standardized and summed to create an overall safety score.

Parent scores from the social involvement subscale were used to create the social involvement variable.

Census Variables. The NICHD Study of Early Child Care and Youth Development collected block-level census data on children's neighborhood characteristics. Four of these census variables were used for the present study – percentage of adults aged 25 or older with a high school degree, percentage of single mothers with children less than age 18, percentage of owner-occupied homes, and overall unemployment rate.

School

Both teachers and principals completed questionnaires during the 3rd grade wave of data collection. The questionnaires are based on the U.S. Department of Education's Schools and Staffing Survey (U.S. Department of Education, 1994, 1999).

FRPL and School-Wide Conduct Problems. The principal's version of the questionnaire requests general information about the school the target child attends, including demographics, staffing, professional development practices, and curriculum. It is a 28-item questionnaire. From this questionnaire it is possible to calculate the percentage of students receiving free or reduced price lunch and to determine the level of school-wide delinquency/conduct problems.

Teacher Education/Qualifications. Teachers completed an analogous version of this same questionnaire, similarly adapted from the Schools and Staffing Survey. The 36-item Teacher Questionnaire requested information about general demographics, the child's classroom, the instructional program, and the support and challenges perceived by the teacher. From this survey it is possible to determine the teacher's level of educational background and certification status.

Teacher Efficacy. Teachers also completed the Teacher Self-Efficacy Scale (Bandura, 1986), a 21-item measure that ascertained teachers' abilities to access school resources, teach effectively, discipline effectively, and create a positive school environment. Cronbach's alphas ranged from .77-.87.

Classroom Climate. Lastly, observational data within each study child's classroom was used to assess classroom-level variables. The Classroom Observation System (COS) is a multi-level observation procedure that tracks student and teacher behaviors. A 30-seconds-on, 30-seconds-off time sampling schedule with 10 minute cycles was used. One observation typically consisted of 8 cycles which were interrupted by more global ratings of the classroom. The system also includes a set of global 7-point scales that assess qualities of the classroom environment. During these global rating periods observers evaluated teacher sensitivity, teacher detachment, teacher overcontrol, classroom management, and positive and negative emotional environment. In combination these measures created the classroom climate composite variable. Reliability was measured through the Pearson correlation coefficient (.69) and repeated-measures ANOVA (.79). The COS-3was based on the COS-1 which was developed by the SECC Steering Committee for the NICHD Study of Early Child Care. The COS-1 was based on the Kindergarten Cos which was developed for the Kindergarten Transition Study (NICHD SECCYD, CCDR 306, 2000).

Outcome Variables

Four outcome variables were examined: cognitive/academic skills, internalizing behaviors, externalizing behaviors, and social skills. In order to take advantage of the multiple methods and informants used to collect the outcome data of interest, *z* scores for each sub-measure of cognitive/academic abilities, internalizing problems, externalizing problems, and social skills were calculated. From there, *z* scores within each outcome domain were summed to create the four composite scores. All outcome variables were measured when children were in 4^{th} grade.

Cognitive/Academic Abilities

In 4^{th} grade the teacher completed a 19-item mock report card for the target child (Pierce, Hamm, & Vandell, 1999). Mean responses from two subscales of this report were used to calculate an overall score. The "current school performance" subscale assesses children's performance in each of six subject areas – reading, oral language, written language, math, social studies, and science. Teachers respond on a 1 (below grade level) to 5 (excellent) scale. The "work habits' subscale obtains information about the child's classroom work habits. Again, teachers respond on a 1 (very poor) to 5 (very good) scale. Reliabilities for the questionnaire are very good, ranging from .92-.94 on the performance subscale and .93-.96 on the work habits subscale (NICHD SECCYD, CCDR 465, 2003; Vandell & Pierce, 1998).

The student's primary teacher also completed the Academic Skills Survey, an adapted version of the measure developed by Meisels, Nicholson, and Atkins-Burnett (1997) for the Early Childhood Longitudinal Study. This is the best available standardized survey of children's academic skills (NICHD SECCYD, CCDR 473, 2003). Part I of the questionnaire assesses the child's language and literacy skills while Part II assesses the child's mathematical thinking skills.

Teachers are told to rate the child's current performance in relation to other children his/her age. Responses range from 1 (not yet: child does not demonstrate skill) to 5 (proficient: child demonstrates skill consistently and competently). Reliabilities for Part I range from .94-.95 while reliabilities for Part II range from .91-.92. A total academic skills score is available from the subtests.

Children completed the Wechsler Abbreviated Scale of Intelligence (WASI, Psychological Corporation, 1999), a short and reliable measure of general cognitive abilities for 6-89 year-olds. The test consists of four subtests: vocabulary, block design, similarities, and matrix reasoning. A full-scale IQ score can be computed from these subscales. The WASI has been standardized on a national sample of over 2000 adults and children. Full-scale IQ scores can range from 62 to 147 with higher scores indicating greater cognitive abilities.

Externalizing and Internalizing Behaviors

Parents and teachers completed the Child Behavior Checklist (CBCL, Achenbach, 1991) when the target child was in 4th grade. Both parent and teacher versions ask respondents to rate the incidence of approximately 100 child behaviors on a 3 point scale (0 = not true of child, 2 = very true of child). According to NICHD, the CBCL is the most widely used screening instrument for identifying problem behaviors in children. NICHD reports that the questionnaire is highly reliable and internally consistent.

Social Skills

In 4th grade the target child and his/her best friend were brought to the lab and videotaped during four interactive play segments – free play, plan a party, snack, and pickup sticks. Observers coded the interactions based on 6 subscales (target child's positive social behavior, target child's negative social behavior, target child's skillful leadership, positive interaction between dyad, negative interaction between dyad, and overall friendship quality). Based on the subscale scores of the four tasks an overall friendship interaction score was created. The codes for this task were adapted by Alhusen, Flyr, Parke, & Clarke-Stewart (2003) from those developed by Flyr, Howe, and Parke (1995) and from the work of earlier researchers, including Gottman (1989), Youngblade, Park, and Belsky (1993), and Dishion, Patterson, and Griesler (1994) to assess the observed quality of friendship. The Total Friendship Interaction Score has moderate internal reliability, $\alpha = .79$.

In addition, parents (38 items) and teachers (30 items) completed the Social Skills subscale of the Social Skills Rating System (Gresham & Elliot, 1990). Respondents were asked to rate the perceived frequency of specific behaviors related to the child's social competence and adaptive functioning. Response categories ranged from 0 (never) to 2 (very often). The Social Skills Scale taps into four sub-components: cooperation, assertion, responsibility, and self control. The scale is correlated with the Social Behavior Assessment, the Child Behavior Checklist, and the Harter Teaching Rating Scale. Reliability is adequate, $\alpha = .81$-$.95$.

Analytic Strategy and Power Analysis

In order to assess the proposed model of cumulative ecological risk a number of analyses were required. To begin, I used multiple imputation to manage problems with missing data. With a nearly complete dataset, risk variables were then correlated with aggregated outcome scores to confirm their predictive roles on an individual level. Next, dichotomization rules were applied and a score of either 0 or 1 was assigned to each case for each risk variable. By summing the total number of risks each child experienced within each domain, and across all domains, regression analyses could be used to determine the predictive power of cumulative risk on each outcome and the impact of interactions between risk domains.

As a further step in testing the ecological cumulative risk model, structural equation modeling was used to fit two measurement models. The first model assumes domain does not matter and creates only one latent risk variable. The second model assumes domain is relevant and develops the domains as depicted in Figure 4.

Lastly structural equation modeling was used to fit a path model predicting outcomes using demographic and parenting risk. This model was used to assess the possibility of mediation through proximal context.

As mentioned previously, a key advantage to this study is its large sample size. In order to validate the analyses used herein I calculated statistical power for each of the regression techniques. The largest regression model used 8 predictor variables (2 controls, 6 CR domains). In order to detect a small effect size at $\alpha = .05$, $\beta = .80$ with 8 independent variables, a sample size of 759 would be required (Faul, Erdfelder, Lang, & Buchner, 2007). Furthermore, in order to detect small effect sizes for two-way interactions using a total of 5 predictors (2 control variables, 2 CR domain main effects, 1 interaction effect), a sample size of 1078 is sufficient. The complete statistical analysis behind this calculation is further explained in the interaction subsection of the results.

RESULTS

Missing Data

Since data were collected over multiple time points and from multiple sources, missing responses and attrition were an inevitable problem. At the month 1 time point 1364 children had been identified for the study. However, by the time children were in third and fourth grade 257 cases did not have data for any of the individual risk variables past year 1 or any of the outcome variables. After thoughtful inspection, these 257 cases along with an additional 29 cases were dropped from subsequent analyses. These cases were missing data on at least half of the necessary variables, i.e. all variables in at least 3 domains (5 risk domains and outcomes). Under this criterion 1078 cases with varying amounts of available data remained (see Table 1). These 1078 cases were then subjected to multiple imputation procedures in order to maximize the number of cases available for statistical analysis.

Using the multiple imputation method in SPSS 19, the original dataset with missing values was used to generate several other datasets with plausible estimates. Depending on the measurement level of variables imputation is determined via logistic or linear regression. For the purposes of this study seven iterations were used to produce seven plausible datasets (SPSS Statistics 19.0, 2010). Constraints on the imputation methods were used such that some variables were used as only predictors in the model (i.e. site of data collection, gender), some variables were used only as dependent variables (i.e. school-wide conduct problems, neighborhood census variables), and some variables were used in both capacities (i.e. income-to-needs, maternal education, outcomes). By specifying constraints like this the number of estimated parameters could be reduced such that a reasonably sized model could be run.

The original data were scanned to determine the best imputation method, specifically whether data indicated a monotone or non-monotone pattern of missingness (SPSS 19.0, 2010). In this case fully conditional specification was utilized because missingness was deemed arbitrary. After imputation the data could be analyzed using a set of pooled output from the newly created datasets.

The multiple imputation technique is currently considered among the best methods for dealing with missing data. Listwise and pairwise deletion, single imputation methods (i.e. mean substitution), and hot-deck substitution are acceptable only in limited instances. Instead, recent years have seen a large push for researchers to use more sophisticated methods with less bias (Acock, 2005).

Attrition Analyses

Independent samples t-tests were used to determine if those who did not complete enough waves of data collection to qualify for inclusion in this study differed significantly from those retained. With regard to income-to-needs at month 1, the families of retained subjects scored significantly higher (M = 3.02) than the families of those not retained (M = 2.25), $t(431) = 4.48$, $p < .01$. Similar results were true for maternal education at month 1. The mothers of retained subjects had significantly higher levels of education (M=14.44 years) compared to those who were not included (M=13.45 years), $t(435) = 5.89$, $p < .01$. Such results are typical of longitudinal studies as it is more difficult to retain low income families due to their mobility, among other things. These findings suggest that the sample, which began as predominantly middle class Caucasian families, is even more inclined in that direction. This should be kept in mind throughout the paper as results may downwardly bias the effects of risk, particularly given the tendency for low income children to experience higher levels of risk (Evans, 2004).

Table 1

Number of Imputed Cases for All Variables Used to Calculate Predictors and Outcomes

Risk Domain	**Variable**	**Variable subcomponents**	**Original dataset**	**Imputed dataset**	**Total cases imputed**
Demographics	Income to needs	Inc-nds 1m	1011	1078	67
		Inc-nds 6m	1046	1078	32
		Inc-nds 15m	1042	1078	36
		Inc-nds 24m	1024	1078	54
		Inc-nds 36m	1042	1078	36
		Inc-nds 54m	1000	1078	78
		Inc-nds K	968	1078	110
		Inc-nds G1	942	1078	136

Risk Domain	Variable	Variable subcomponents	Original dataset	Imputed dataset	Total cases imputed
		Inc-nds G3	982	1078	96
	Child race	Child ethnicity	1078	1078	0
		Child Hispanic	1078	1078	0
	Maternal education	Mother education 36m	1045	1078	33
	Maternal age at birth of first child	Mother age, 1 month	1078	1078	0
		Child birth order, 1 month	1078	1078	0
		Mother age at child's birth	1071	1071	0
	Maternal marital status	Mother marital status	1035	1078	43
		Father in hshold	1058	1058	0
Home environment	Instability	Residential moves	740	1078	338
	Maternal depression	Maternal depression	1026	1078	52
	Parent relationship quality	Relationship satisfaction	1014	1078	64
	Housing quality	HOME physical environment	983	1078	95
		HOME learning materials	985	1078	93
		Literacy environment	1016	1078	62
	Chaos	CHAOS	1027	1078	51
Parenting	Attachment	Felt security	982	1078	96
		Total positive relationship	1027	1078	51
	Responsiveness	HOME responsivity	1001	1078	77
		HOME acceptance	1005	1078	73
	Warmth	Maternal supportive presence	982	1078	96
		Emotional quality	1012	1078	66
	Hostility	Hostility	982	1078	96
	Cognitive stimulation	Maternal stimulation	982	1078	96
Neighborhood	Safety	Mother questionnaire	1029	1078	49
		Child questionnaire	1016	1078	62
	Social involvement	Social involvement	1021	1078	57
	% Owner occupied housing	% owner occupied housing	1071	1078	7
	% High school graduates	% 25+ with hs degree	1071	1078	7
	% Single moms	% with children <18	1071	1078	7
	% Unemployment	% unemployed	1071	1078	7
School	Free and reduced price lunch	Total current enrollment at school	808	1078	270

Risk Domain	Variable	Variable subcomponents	Original dataset	Imputed dataset	Total cases imputed
		# students FRPL eligible	746	1078	332
	Teacher education	Masters degree?	973	1078	105
		Teaching certificate?	912	1078	166
	Teacher efficacy	Teacher self-efficacy	969	1078	109
	School-wide conduct problems	Student tardiness	810	1078	268
		Student absenteeism	811	1078	267
		Teacher absenteeism	810	1078	268
		Physical conflict among students	810	1078	268
		Robbery or theft	812	1078	266
		Vandalism of school property	805	1078	273
		Verbal abuse of teachers	811	1078	267
		Disrespect for teachers	810	1078	268
		Student apathy	808	1078	270
		Lack of parent involvement	811	1078	267
		Students unprepared to learn	812	1078	266
		Poor student health	812	1078	266
	Classroom quality	Classroom quality	962	1078	116
Outcomes	Cognitive/Academic	WASI IQ	1002	1078	76
		School performance	917	1078	161
		Work habits	925	1078	153
		Academic Skills	901	1078	177
	Externalizing	Mother CBCL	1011	1078	67
		Teacher CBCL	909	1078	169
	Internalizing	Mother CBCL	1011	1078	67
		Teacher CBCL	909	1078	169
	Social skills	Mother SSRS	1009	1078	69
		Teacher SSRS	901	1078	177
		Friendship interaction	889	1078	189

Validation of Risk Factors

Each individual risk variable was examined to determine its relationship with the outcome variables. Two criteria were necessary for inclusion of risk variables in the overall model, 1 - a significant correlation with at least 2 of the 4 outcome domains, 2 – correlations in theoretically predicted directions. See Table 2 for correlation statistics.

All but two of the 26 risk variables met these criteria. Free and reduced price lunch status and teacher qualifications, both school-level variables, were not significantly correlated with any of the outcome measures. As a result these two variables were not used in subsequent analyses. Accordingly, the school risk domain contained only three risk variables rather than the proposed five. The likely explanation for a lack of association between the risk variables and outcomes is a problem of restricted range. 88% of teachers possessed either a Masters degree or a teaching certification while only 10% of schools had 60% or more of students who qualified for free or reduced price lunch.

Table 2

Bivariate Correlations Between Risk and Outcome Variables

Variable	Inc-nds	Child Race	Mom Educ	Mom Age	Mom Depress	Married	Housing Quality	Chaos	Parent Rel Quality	Instability	Warmth	Respon-siveness
Inc-nds	1.00 (1078)	-.278** (1078)	.536** (1078)	.555** (1027)	-.234** (1078)	.215** (837)	.404** (1078)	-.143** (1078)	.106** (870)	-.273** (1078)	.328** (1078)	.189** (1078)
Child Race		1.00 (1078)	-.238** (1078)	-.321** (1078)	.107** (1078)	-.137** (837)	-.279** (1078)	-.018 (1078)	-.024 (1078)	229** (1078)	-.215** (1078)	-.176** (1078)
Mom Educ			1.00 (1078)	.564** (1027)	-.232** (1078)	.241** (837)	.425** (1078)	-.123** (1078)	.058 (870)	-.249** (1078)	.334** (1078)	.229** (1078)
Mom Age				1.00 (1027)	-.200** (1027)	.273** (797)	.447** (1027)	-.099** (1027)	-.019 (828)	-.371** (1027)	.282** (1027)	.188** (1027)
Mom Depress					1.00 (1078)	-.143** (837)	-.234** (1078)	.345** (1078)	-.410** (870)	.182** (1078)	-.172** (1078)	-.165** (1078)
Married						1.00 (837)	.205** (837)	-.019 (837)	.009 (782)	-.342** (837)	.224** (837)	.154** (837)
Housing Quality							1.00 (1078)	-.141** (1078)	.095* (870)	-.274** (1078)	.295** (1078)	.287** (1078)
Chaos								1.00 (1078)	-.328** (870)	.013 (1078)	-.112** (1078)	-.125** (1078)
Parent Rel Quality									1.00 (870)	.068* (870)	.087* (870)	.115** (870)
Instability										1.00 (1078)	-.169** (1078)	-.137** (1078)
Warmth											1.00 (1078)	.315** (1078)
Respon-siveness												1.00 (1078)

	Inc-nds	Child Race	Mom Educ	Mom Age	Mom Depress	Married	House Quality	Chaos	Parent Rel Quality	Instability	Warmth	Respon-siveness
Attachment												
Hostility												
Cog Stim												
FRPL												
Teacher qualifications												
Tchr efficacy												
Classroom climate												
Conduct problems												
Safety												
HS grads												
Single moms												
Owner occ. Housing												
Unemploy-Ment												
Social involvement												
Academics												
Internalizing												
Externalizing												
Social Skills												

	Attach-ment	Hostility	Cog Stim	FRPL	Teacher qualific-ations	Tchr Efficacy	Class-room Climate	Conduct Problems	Safety	HS grads	Single moms	Owner occ. Housing	Unempl oyment	Social involve ment
Inc-nds	.172** (1078)	-.124** (1078)	.398** (1078)	-.197 (1078	.046 (1078)	.160** (1078)	.196** (1078)	-.394** (1078)	.362** (1078)	.375** (1078)	-.317** (1078)	.241** (1078)	-.208** (1078)	.183** (1078)
Child Race	-.051 (1078)	.040 (1078)	-.270** (1078)	.111 (1078)	-.045 (1078)	-.036 (1078)	-.174** (1078)	.195** (1078)	-.338** (1078)	-.287** (1078)	.367** (1078)	-.196** (1078)	.295** (1078)	-.132** (1078)
Mom Educ	.171** (1078)	-.151** (1078)	.441** (1078)	-.167 (1078)	.047 (1078)	.124** (1078)	.182** (1078)	-.311** (1078)	.354** (1078)	.355** (1078)	-.242** (1078)	.201** (1078)	-.170** (1078)	.126** (1078)
Mom Age	.112** (1027)	-.120** (1027)	.364** (1027)	-.142 (1027)	.082* (1027)	.075* (1027)	.161** (1027)	-.319** (1027)	.330** (1027)	.308** (1027)	-.229** (1027)	.121** (1027)	-.210** (1027)	.155** (1027)
Mom Depress	-.284** (1078)	.197** (1078)	-.205** (1078)	.090 (1078)	.002 (1078)	-.129** (1078)	-.123** (1078)	.160** (1078)	-.240** (1078)	-.155** (1078)	.151** (1078)	-.101** (1078)	.082** (1078)	-.155** (1078)
Married	.084* (837)	-.149** (837)	.212** (837)	-.075 (837)	.020 (837)	.055 (837)	.063 (837)	-.131** (837)	.135** (837)	.121** (837)	-.172** (837)	.092* (837)	-.103* (837)	.069 (837)
House Quality	.124** (1078)	-.095** (1078)	.357** (1078)	-.150 (1078)	.047 (1078)	.112* (1078)	.156** (1078)	-.222** (1078)	.334** (1078)	.314** (1078)	-.279** (1078)	.173** (1078)	-.196** (1078)	.245** (1078)
Chaos	-.288** (1078)	.119** (1078)	-.073* (1078)	.048 (1078)	.013 (1078)	-.047 (1078)	-.015 (1078)	.082* (1078)	-.151** (1078)	-.067* (1078)	.014 (1078)	-.015 (1078)	.007 (1078)	-.102** (1078)
Parent Rel Quality	.197** (870)	-.104** (870)	.080* (870)	.000 (1078)	-.044 (1078)	.062 (870)	.059 (870)	-.035 (870)	.098** (870)	.047 (870)	-.030 (870)	.051 (870)	-.014 (870)	.130** (870)
Instability	-.115** (1078)	.109** (1078)	-.194** (1078)	.099 (1078)	.010 (1078)	-.084* (1078)	-.103** (1078)	.163** (1078)	-.157** (1078)	-.118** (1078)	.221** (1078)	-.161** (1078)	.112** (1078)	-.064* (1078)
Warmth	.464** (1078)	-.388** (1078)	.552** (1078)	-.096 (1078)	.039 (1078)	.118** (1078)	.170** (1078)	-.184** (1078)	.306** (1078)	.245** (1078)	-.189** (1078)	.144** (1078)	-.144** (1078)	.087** (1078)
Responsive ness	.255** (1078)	-.198** (1078)	.289** (1078)	-.056 (1078)	.011 (1078)	.105** (1078)	.145** (1078)	-.177** (1078)	.238** (1078)	.210** (1078)	-.147** (1078)	.062* (1078)	-.107** (1078)	.141** (1078)
Attachment	1.00 (1078)	-.452** (1078)	.369** (1078)	-.048 (1078)	-.044 (1078)	.126** (1078)	.116** (1078)	-.108* (1078)	.182** (1078)	.081* (1078)	-.079* (1078)	.096** (1078)	-.061* (1078)	.064* (1078)
Hostility		1.00 (1078)	-.309** (1078)	.026 (1078)	.037 (1078)	-.076* (1078)	-.085* (1078)	.044 (1078)	-.151** (1078)	-.092* (1078)	.031 (1078)	-.054 (1078)	.054 (1078)	-.037 (1078)
Cog Stim			1.00 (1078)	-.127 (1078)	.011 (1078)	.130** (1078)	.155** (1078)	-.238** (1078)	.300** (1078)	.303** (1078)	-.211** (1078)	.141** (1078)	-.151** (1078)	.136** (1078)

	Attach-ment	Hostility	Cog Stim	FRPL	Teacher qualifi-cations	Tchr Efficacy	Class-room Climate	Conduct Problems	Safety	HS grads	Single moms	Owner occ. Housing	Unempl oyment	Social involve ment
FRPL				1.00 (1078)	-.001 (1078)	-.074 (1078)	-.089 (1078)	.225 (1078)	-.147 (1078)	-.172 (1078)	.126 (1078)	-.101 (1078)	.087 (1078)	-.046 (1078)
Teacher qualify					1.00 (1078)	-.026 (1078)	.089** (1078)	-.020 (1078)	-.026 (1078)	.068 (1078)	.013 (1078)	.019 (1078)	-.014 (1078)	.060 (1078)
Teacher Efficacy						1.00 (1078)	.196** (1078)	-.128** (1078)	.125** (1078)	.160** (1078)	-.104** (1078)	-.005 (1078)	-.046 (1078)	.090* (1078)
Classroom Climate							1.00 (1078)	-.178** (1078)	.165** (1078)	.215** (1078)	-.190** (1078)	.107** (1078)	-.200** (1078)	.089** (1078)
Conduct Problems								1.00 (1078)	-.241** (1078)	-.334** (1078)	.232** (1078)	-.177** (1078)	.156** (1078)	-.120** (1078)
Safety									1.00 (1078)	.340** (1078)	-.337** (1078)	.258** (1078)	-.300** (1078)	.219** (1078)
HS grads										1.00 (1078)	-.384** (1078)	.302** (1078)	-.439** (1078)	.121** (1078)
Single moms											1.00 (1078)	-.578** (1078)	.511** (1078)	-.153** (1078)
Owner Occ. Housing												1.00 (1078)	-.359** (1078)	.138** (1078)
Unemploy-ment													1.00 (1078)	-.088** (1078)
Social involve-ment														
Academics														
Intern-alizing														
Extern-alizing														
Social														

	Academics	Internalizing	Externalizing	Social
Inc-nds	.405** (1078)	-.163** (1078)	-.267** (1078)	.282** (1078)
Child Race	-.322** (1078)	.018 (1078)	.172** (1078)	-.244** (1078)
Mom Educ	.456** (1078)	-.151** (1078)	-.270** (1078)	.286** (1078)
Mom Age	.398** (1027)	-.124** (1027)	-.249** (1027)	.248** (1027)
Mom Depress	-.234** (1078)	.286** (1078)	.321** (1078)	-.245** (1078)
Married	.210** (837)	-.021 (837)	-.176** (837)	.135** (837)
House Quality	.374** (1078)	-.124** (1078)	-.276** (1078)	.298** (1078)
Chaos	-.157** (1078)	.143** (1078)	.250** (1078)	-.216** (1078)
Parent Rel Quality	.066 (870)	-.129** (870)	-.151** (870)	.150** (870)
Instability	-.210** (1078)	.116** (1078)	.227** (1078)	-.186** (1078)
Warmth	.400** (1078)	-.152** (1078)	-.327** (1078)	.395** (1078)
Responsiveness	.238** (1078)	-.081* (1078)	-.265** (1078)	.319** (1078)
Attachment	.255** (1078)	-.260** (1078)	-.432** (1078)	.420** (1078)
Hostility	-.180** (1078)	.057 (1078)	.223** (1078)	-.250** (1078)
Cog Stim	.443** (1078)	-.113** (1078)	-.268** (1078)	.317** (1078)

	Academics	Internalizing	Externalizing	Social
FRPL	-.117 (1078)	.010 (1078)	.086 (1078)	-.097 (1078)
Teacher qualifications	.059 (1078)	-.013 (1078)	-.032 (1078)	.009 (1078)
Tchr Efficacy	.139** (1078)	-.030 (1078)	-.113** (1078)	.141** (1078)
Classroom Climate	.219** (1078)	-.088** (1078)	-.231** (1078)	.191** (1078)
Conduct Problems	-.213** (1078)	.055 (1078)	.176** (1078)	-.148** (1078)
Safety	.348** (1078)	-.187** (1078)	-.241** (1078)	.258** (1078)
HS grads	.254** (1078)	-.110** (1078)	-.204** (1078)	.175** (1078)
Single moms	-.254** (1078)	.095** (1078)	.191** (1078)	-.195** (1078)
Owner Occ. Housing	.159** (1078)	-.081* (1078)	-.175** (1078)	.138** (1078)
Unemployment	-.181** (1078)	.027 (1078)	.156** (1078)	-.112** (1078)
Social involvement	.127** (1078)	-.090* (1078)	-.155** (1078)	.133** (1078)
Academics	1.00 (1078)	-.257** (1078)	-.409** (1078)	.514** (1078)
Internalizing		1.00 (1078)	.450** (1078)	-.330** (1078)
Externalizing			1.00 (1078)	-.570** (1078)
Social				1.00 (1078)

*= p < .05, **=p < *.01*

Validation of Domains: Factor Analysis

Prior to calculating a total CR score for each domain, I used factor analysis to support the hypothesized structure empirically. Principal components factor analysis with varimax rotation was used to determine if the 24 variables represented more than one underlying factor. Initial tests indicated that the observed variables were indeed suited to some form of added structure, Kaiser-Meyer-Olkin Measure of Sampling Adequacy = 847; Bartlett's Test of Sphericity, χ^2 = 4344, $p < .01$.

The rotated component matrix is displayed in Table 3. Based on these results, a factor structure that merged best with both theory and the observed data was determined. Component 1 can be identified as demographic risk while Component 2 is clearly parenting risk. Neighborhood variables loaded highly on factor 3, supporting a neighborhood factor. Two of the three proposed school risk variables loaded highly on Component 7. Interestingly, the home environment variables were spread across three factors. Household chaos, maternal depression, and parent relationship quality all loaded highly on Component 4 while instability and marital status (initially proposed as a demographic risk factor) loaded highly on Component 6. Lastly, the quality of the home environment was the best indicator of Component 5.

Based on these results I shifted the maternal marital status variable from the demographic domain to the home environment domain. I further sub-divided home environment into two factors: emotional and physical home. Because CR models drastically minimize information I opted to combine the quality of the home environment with the more structural home factor (Component 6) in order to have more variables in each domain rather than an extra domain with only one variable. This decision was also based upon considerations for structural equation modeling which necessitates at least three observed variables for each latent variable (Kline, 2005).

Table 3

Factor Loadings for the 24 Risk Variables Using Principal Components Factor Analysis with Varimax Rotation

	Component						
	1	2	3	4	5	6	7
Maternal education	.751	.172	.051	.070	.146	.140	-.001
Mother age at birth of 1st child	.704	-.013	-.012	.012	.191	.362	-.054
Child race	-.065	-.106	-.364	.132	-.345	-.277	.082
Average income-to-needs	.715	.087	.137	.149	.106	.122	.144
Parents married, father/step-father in home	.152	.169	.061	.049	.050	.698	.026
Maternal depression	-.132	-.076	-.039	-.720	-.108	-.160	-.045
CHAOS	-.161	-.104	.019	-.686	-.093	.112	.105
Parent relationship quality	-.075	.076	.089	.677	.019	.006	.122
Instability	-.130	-.025	-.092	-.008	.000	-.810	-.040
Quality of home environment	.413	.026	.091	.134	.505	.193	.004
Maternal hostility	.016	-.734	.007	-.099	.032	-.052	.004
Maternal cognitive stimulation	.389	.584	.083	-.048	.155	.086	-.012
Maternal warmth	.245	.704	.074	.015	.101	.068	.083
Attachment	-.006	.718	.023	.326	-.128	.018	.110
Maternal responsiveness	.002	.452	.044	-.020	.412	.104	.017
Teacher self-efficacy	-.005	.041	-.087	.034	.110	.070	.840
School-wide conduct problems	-.629	-.083	-.242	-.030	.149	.080	-.112
Classroom climate	.170	.078	.175	.038	.017	-.018	.610
Neighborhood social involvement	.031	-.069	.021	.126	.720	-.066	.100
% single moms w/ kids <18	-.135	.017	-.777	-.099	-.057	-.169	-.117
% owner occupied houses	.060	.021	.763	.098	-.036	.019	-.014
% unemployed	-.113	-.049	-.685	.014	-.130	-.005	-.006
% age 25+ w/ high school degree	.448	.172	.433	-.086	.254	-.059	.164
Neighborhood safety	.269	.203	.267	.137	.460	.014	.090

Dichotomization of Risk Factors

Having validated the importance of each individual variable as well domain structure, the next step involved assigning a score of 1 or 0 to each case on each risk variable. A score of 0 indicates no risk on that variable while a score of 1 indicates that the child fell within the upper quartile of the sample or some other pre-determined, theoretically supported rationale. A description of the dichotomization cut-off criteria for each variable along with a breakdown of the number and percentage of the sample at risk on each variable is provided in Table 4.

Next I used each child's dichotomized risk scores to create cumulative risk indices across the six risk domains. In other words, each case could score between 0 and 4 on demographic CR, 0-3 on physical home environment CR, 0-3 on emotional home environment CR, 0-5 on parenting CR, 0-3 on school CR, and 0-6 on neighborhood CR

Table 4

Criteria Used to Dichotomize Risk Variables

Risk Domain	**Variable**	**Risk assigned if:**	**Total # sample at risk**	**Total % sample at risk**
Demographics	Income to needs	Average inc-to- nds ≤2.0	282	26.2%
	Child race	Black or Hispanic	187	17.3%
	Maternal education	Less than high school degree	61	5.7%
	Maternal age at birth of first child	18 or younger	104	10.1%
Home environment (physical)	Maternal marital status	Mother not married and living with father/adoptive parent	353	32.7%
	Instability	Score ≥15	306	28.4%
	Housing quality	Sum of z scores <-1.2073	269	25.0%
Home environment (emotional)	Maternal depression	CES-D score ≥16	208	19.3%

Risk Domain	Variable	Risk assigned if:	Total # sample at risk	Total % sample at risk
	Chaos	Score of 21 or higher on CHAOS	294	27.3%
	Maternal satisfaction	Score less than 3.1931	236	25.3%
Parenting	Attachment	Sum of z scores ≤ -.9211	265	24.6%
	Responsiveness	Sum of scores <15	221	20.5%
	Warmth	Sum of z scores < -.791	265	24.6%
	Hostility	Hostility score ≥3	83	7.7%
	Cognitive stimulation	Maternal stimulation < 8		
Neighborhood	Safety	Sum of z scores < -.8710	269	25%
	Social involvement	Social involvement <3	269	25%
	Owner occupied housing	< 58.7% owner occupied	269	25%
	High school grads	< 80%	267	24.8%
	Single moms	≥25%	70	6.5%
	Unemployment	≥ 10%	83	7.7%
School	Classroom quality	Score < 26.5	265	24.6%
	Teacher efficacy	Efficacy score <120	272	25.2%
	School-wide conduct problems	Average conduct problem score >2	230	21.3%

In order to determine if one variable was carrying the weight for the cumulative risk index in each domain I conducted regression analyses that tested CR in each domain along with each variable measured on a continuous scale. Interestingly, a handful of variables did present problems in this context, particularly with regard to internalizing outcomes. For example, when maternal depression and emotional home environment CR were entered into a regression equation, the CR domain effect became non-significant for all outcomes except externalizing behaviors. The same was true for all of the physical environment variables with regard to internalizing behaviors. Also problematic were attachment, classroom climate, and school-wide conduct problems. When each of these variables were entered into a regression equation with their corresponding CR variable, the CR variable became insignificant for internalizing behaviors. As a result of these analyses, I present findings from the other three outcome variables first and then turn my focus to internalizing behaviors.

Regression Analyses

Control Variables

Child sex significantly impacted two of the four outcome variables, academic skills, $t(1077) = 3.21$, $p < .01$, and social skills, $t(1077) = 6.73$, $p < .01$. As a result, sex was used as a control variable in all subsequent analyses with these outcomes. Furthermore, because prior levels of the outcome variables could be carrying any effects of cumulative risk, Grade 3 outcome variables were used as a further control variable. Except for social skills, the measures used in 3^{rd} grade were identical to those used in 4^{th} grade (i.e. Mock Report Card, Academic Skills Survey, IQ test, parent and teacher-reported CBCL). Two of the three social skills variables were identical. However, the Friendship Interaction was not available at Grade 3. As with the Grade 4 outcomes, scores on each of the individual measures in Grade 3 were standardized and summed to create an aggregated score.

Total Cumulative Risk Index

To assess the impact of total amount of risk, regardless of domain, demographic CR, physical home environment CR, emotional home environment CR, parenting CR, school CR, and neighborhood CR were summed. Using hierarchical linear modeling, the appropriate control variables were entered in step 1 of the model. In step 2 each of the aggregate outcome variables was regressed on the total CR score.

Total cumulative risk was negatively associated with both academic, t (1077) = -9.07 $p <$ .01, B = -.13, β = -.19 and social outcomes, t (1077) = -8.43, $p < .01$, B = -.12, β = -.22, and positively related to externalizing problems, t (1077) = 15.04, $p < .01$, B = 1.51, β = .37.

Domain-Specific Cumulative Risk

Next I used hierarchical linear regression to determine the degree to which each domain predicted each outcome when controlling for the other risk domains, child gender, and prior outcome levels. These results are presented in Table 5. Because maternal depression was a problematic variable for nearly all outcome domains I present results with and without this variable included in the emotional home environment domain. Although predictive at an individual/continuous level, the deletion of maternal depression from the emotional home CR domain did not drastically change the ecological domains regression results.

Compared to the total cumulative risk model, the domain-specific CR approach explained 0.5% more variance in academic skills, 1% more variance in social skills, and 1% more variance in externalizing problems. Parenting, the most proximal domain, was the most consistent predictor of outcomes. On the other hand, in combination with the other domains, school risk tended to add the least predictive power to the models. The domain model explained the greatest proportion of variance in academic outcomes, 70%, compared to 48% and 39% of explained variance in social and externalizing outcomes respectively. The only outcome variable in which all domains were important, even after controlling for the effects of other domains, was externalizing behaviors (marginally significant effect of school risk).

Table 5

Hierarchical Linear Regression Results for Academic Skills, Externalizing Behaviors, Social Skills

Outcome		**Unstandardized Coefficients**		**Standardized**	**t**	**Sig.**
		B	**Std. Error**	**B**		
Academics	*Constant*	0.35 0.35[r]	0.17 0.17[r]		2.04 2.05[r]	.043 .042[r]
	Child sex	0.14 0.14[r]	0.09 0.09[r]	0.03 0.03[r]	1.47 1.43[r]	.142 0.15[r]
	Grade 3 academics	0.73 0.74[r]	0.02 0.02[r]	0.72 0.72[r]	35.94 35.93[r]	.000 .000[r]
	Demographics	-0.29 -0.29[r]	0.07 0.07[r]	-0.11 -0.11[r]	-4.49 -4.49[r]	.000 .000[r]
	Physical home environment	-0.03 -0.03[r]	0.06 0.06[r]	-0.01 -0.01[r]	-0.45 -0.52[r]	.653 .602[r]
	Emotional home Environment	-0.09 -0.09[r]	0.06 0.08[r]	-0.03 -0.02[r]	-1.44 -1.17[r]	.155 .245[r]
	Parenting	-0.11 -0.12[r]	0.05 0.05[r]	-0.05 -0.06[r]	-2.43 -2.53[r]	.017 .013[r]
	School	-0.04 -0.04[r]	0.07 0.07[r]	-0.01 -0.01[r]	-0.55 -0.59[r]	.582 .555[r]
	Neighborhood	-0.14 -0.14[r]	0.05 0.05[r]	-0.07 -0.07[r]	-3.05 -3.08[r]	.003 .003[r]
Externalizing	*Constant*	63.65 63.57[r]	1.66 1.66[r]		38.42 38.20[r]	.000 .000[r]
	Grade 3 externalizing	0.28 0.29[r]	0.02 0.02[r]	0.42 0.42[r]	15.77 15.81[r]	.000 .000[r]

Outcome		**Unstandardized Coefficients** **B**	 **Std. Error**	**Standardized** **B**	**t**	**Sig.**
Externalizing	Demographics	1.34 1.34[r]	0.58 0.58[r]	0.08 0.08[r]	2.33 2.33[r]	.021 .021[r]
	Physical home Environment	1.69 1.79[r]	0.50 0.50[r]	0.11 0.11[r]	3.38 3.57[r]	.001 .000[r]
	Emotional home Environment	2.02 2.14[r]	0.47 0.61[r]	0.11 0.09[r]	4.34 3.53[r]	.000 .000[r]
	Parenting	2.34 2.42[r]	0.39 0.39[r]	0.18 0.19[r]	5.99 6.20[r]	.000 .000[r]
	School	1.02 1.08[r]	0.52 0.52[r]	0.05 0.06[r]	1.95 2.07[r]	.052 .039[r]
	Neighborhood	0.81 0.84[r]	0.35 0.35[r]	0.07 0.07[r]	2.29 2.37[r]	.022 .018[r]
Social Skills	*Constant*	-0.68 -0.67[r]	0.17 0.17[r]		-4.00 -3.91[r]	.000 .000[r]
	Child sex	0.83 0.83[r]	0.09 0.09[r]	0.20 0.20[r]	8.81 8.81[r]	.000 .000[r]
	Grade 3 social skills	0.70 0.70[r]	0.04 0.04[r]	0.51 0.51[r]	19.50 19.51[r]	.000 .000[r]
	Demographics	-0.18 -0.18[r]	0.07 0.07[r]	-0.08 -0.08[r]	-2.49 -2.48[r]	.013 .014[r]
	Physical home environment	-0.12 -0.12[r]	0.07 0.07[r]	-0.05 -0.06[r]	-1.77 -1.85[r]	.078 .066[r]
	Emotional home Environment	-0.04 -0.08[r]	0.07 0.09[r]	-0.02 -0.02[r]	-0.61 -0.87[r]	.544 .389[r]

Outcome		Unstandardized Coefficients B	Std. Error	Standardized B	t	Sig.
Social Skills.	Parenting	-0.25	0.06	-0.15	-4.65	.000
		-0.25[r]	0.05[r]	-0.15[r]	-4.65[r]	.000[r]
	School	-0.03	0.07	-0.01	-0.38	.709
		-0.03[r]	0.07[r]	-0.01[r]	-0.39[r]	.698[r]
	Neighborhood	-0.06	0.05	-0.04	-1.19	.238
		-0.06[r]	0.05[r]	-0.04[r]	-1.19[r]	.237[r]

Note. r represents model without maternal depression variable.

Internalizing Problems

The total (lump sum) CR index was positively related to internalizing behaviors, t (1077) = 6.01, p < .01, B = .77, β = .19.

A number of variables accounted for variance in internalizing behaviors beyond that of their domain CR variable - maternal depression, attachment, conduct problems, and classroom climate. An interaction effect between each of these variables and their respective domains was created and entered into a regression equation to determine how the combination of variables might impact internalizing behavior. After controlling for main effects, maternal depression x emotional home environment CR significantly predicted internalizing behaviors, t(1077) = -2.01, p < .05. Figure 6 shows that when mothers are not depressed, children at moderate and high levels of home risk do not differ much in their internalizing scores. However, when mothers are depressed the children with high levels of risk suffer much more from internalizing problems.

The remaining interaction terms did not significantly predict internalizing outcomes after controlling for main effects: parenting CR x attachment, t(1077) = -.41 , p = 68; school CR x conduct problems, $t(1077) = -.85$, $p = .40$; school CR x classroom climate, $t(1077) = -1.28$, $p = .20$. The general absence of interaction effects between the continuous variables and their respective CR domains seems to support an additive model of risk.

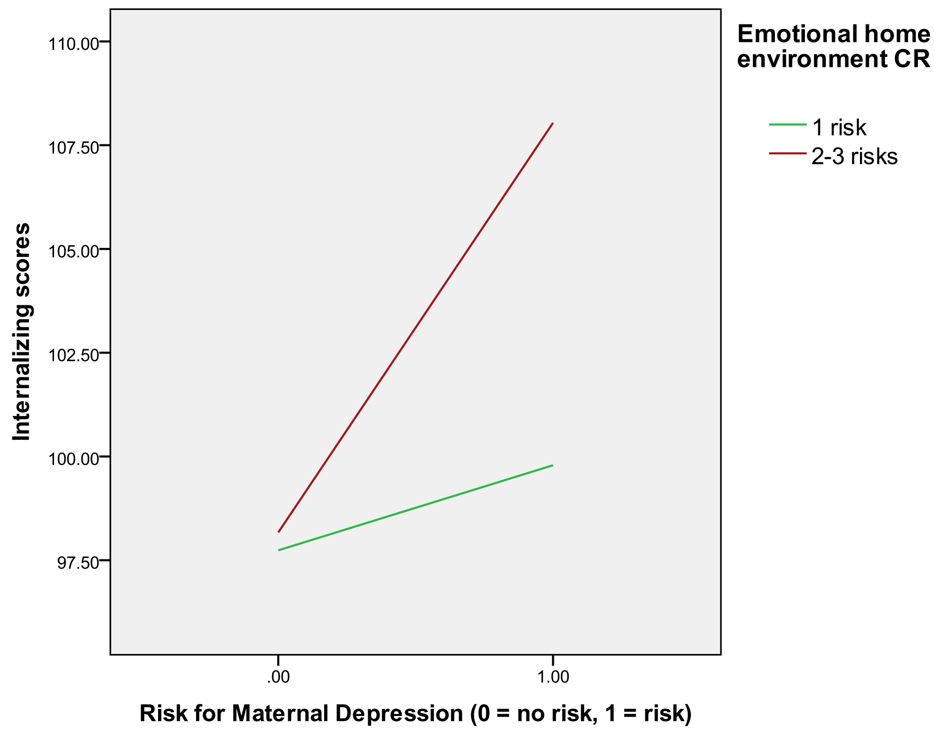

Figure 6. The effect of maternal depression and moderate versus high emotional home environment CR on children's internalizing scores.

As a result of these findings, I recreated the emotional home environment CR variable using only two of the three original variables. Maternal depression was excluded. Internalizing scores were then regressed on the domains using hierarchical linear regression.

The results in Table 6 indicate the contribution of each domain after controlling for the effects of all other domains. Even after controlling for the other risk domains and prior internalizing behaviors, the 2-variable emotional home environment CR metric significantly predicts internalizing scores in 4th grade children. Along with parenting, this is the only significant risk domain for predicting internalizing problems.

Compared to the lump sum model, the domain-specific approach explained 1% more variance in internalizing behaviors.

Table 6

Hierarchical Linear Regression Results for Internalizing Behaviors

Outcome		**Unstandardized Coefficients** **B**	**Std. Error**	**Standardized B**	**t**	**Sig.**
Internalizing	*Constant*	73.46	2.09		35.08	.000
	Grade 3 Internalizing	0.23	0.02	0.35	10.76	.000
	Demographics	1.06	0.74	0.06	1.44	.154
	Physical home environment	0.72	0.56	0.05	1.27	.203
	Emotional home environment	1.87	0.74	0.08	2.54	.012
	Parenting	0.91	0.42	0.07	2.15	.032
	School	-0.08	0.64	-0.00	-0.12	.907
	Neighborhood	0.48	0.41	0.04	1.17	.243

After determining the influence of domain-specific CR on all outcomes I turned to answering question 1a.   In order to determine whether the total number of risks might influence developmental outcomes above and beyond the impact of domain-specific risk I used hierarchical linear regression with all 6 CR domains and the total CR metric as independent variables. After controlling for CR in all domains, the total amount of risk did not add any additional predictive power for explaining academic, internalizing, or social outcomes.

However, it did significantly predict externalizing outcomes, even after controlling for the number of risks in each domain, $t(1077) = 2.29$, $p < .05$.

Interestingly, this same analysis yielded domain-specific effects for social outcomes. After controlling for total CR and the effects of all other CR domains, parenting CR significantly predicted social outcomes, $t(1077) = -2.99$, $p < .05$. It appears that level of parenting risk is particularly relevant when measuring children's social skills.

To summarize findings up to this point, the six domain CR indices added differential predictive power across the four outcome measures. For instance, while emotional home environment and parenting were the only significant predictors of internalizing behavior problems after controlling for the effects of other risk domains, the same was not true for externalizing behaviors. Controlling for the other risk domains, demographics, physical home environment, emotional home environment, parenting, and neighborhood all impacted externalizing behaviors to some extent. Additionally, significant variance in academics and social skills was explained by at least 2 of the 6 risk domains, but the domains differed by outcome. While neighborhood risk influenced academics above and beyond the effects of other domains, it did not have the same power in predicting social outcomes. Conversely, the physical home environment significantly predicted some degree of variance in social outcomes but not in academic outcomes (although this effect is marginally significant, $p = .080$ with maternal depression in model; $p = .07$ without maternal depression in model).

These results suggest there is some validity in creating sub-types of risk rather than simply using a total cumulative risk score. Nevertheless, the total CR still warrants attention. Total CR was predictive of externalizing outcomes, even after controlling for CR in each domain. Thus, in some instances (i.e. social outcomes), domain-specific risk appears to be more important than overall amount of risk experienced, yet in other instances (i.e. externalizing outcomes) the reverse appears true.

Interaction Effects Between Risk Domains

The potential for multiplicative effects of risk domains was assessed through a series of regression equations using interaction effects. For each of the following two-way interaction tests the control variables (child gender, prior outcome level) were entered in the first block of a regression analysis, the two CR domains of interest were entered in the second block, and the interaction effect of those two domains was entered in the third block.

In order to attain sufficient statistical power, main effects as well as interaction terms were reduced to categorical variables (i.e. no risk, low risk, high risk). Such a procedure increased statistical power such that even small effect sizes could be detected. For example, if the continuous nature of CR variables were used, a total of 5 levels of demographic risk (0, 1, 2, 3, 4) and four levels of school risk (0, 1, 2, 3) would be necessary. This creates a 5x4 table with a total of 1058 degrees of freedom for the denominator (1078-20) and 12 degrees of freedom for the interaction. Using power analysis, at $\alpha = .05$, $\beta = .54$. However, if the two CR variables are categorized into no, low, and high risk the interaction becomes a 3x3 table and power at the same alpha value increases to .74 (Cohen, 1988). Such no, low, and high risk categories were used for all subsequent interaction effects in order to attain sufficient power to detect even small interaction effects.

Contrary to expectations, neither demographic CR x physical home environment CR nor demographic CR x emotional home environment CR significantly predicted any of the outcome variables above and beyond the effects of the independent risk domains. Similarly, the demographic CR x parenting CR interaction effect was not significant. See Appendix for detailed statistical data on all interaction effects.

In a similar manner, physical home environment CR x neighborhood CR and emotional home environment CR x neighborhood CR did not significantly predict any of the outcome variables. The same was true for the interaction between both home CR domains and school CR in predicting academic outcomes.

In the interest of thoroughness I tested two additional interaction effects, examining how demographic CR might moderate the effect of the remaining two domains (school and neighborhood CR) on the outcome variables. Demographic CR interacted with school CR but not neighborhood CR. Demographic CR x school CR predicted academic outcomes, t (1077) = 2.87, $p < .05$ and internalizing behaviors, t (1077) = -2.25, $p < .05$.

I examined these two interaction effects with a graph. Figure 7 shows academic outcomes by three levels of demographic risk and three levels of school risk (no risk, low risk, and high risk). As can be seen in Figure 7, the adverse effects of demographic CR on academic achievement are particularly exacerbated in children with no school risk factors. Similarly, Figure 8 shows that the adverse effects of demographic CR are exacerbated in children with no school risk factors. I further examined these interaction effects using guidelines recommended by Jaccard, Wan, & Turrisi (1990).

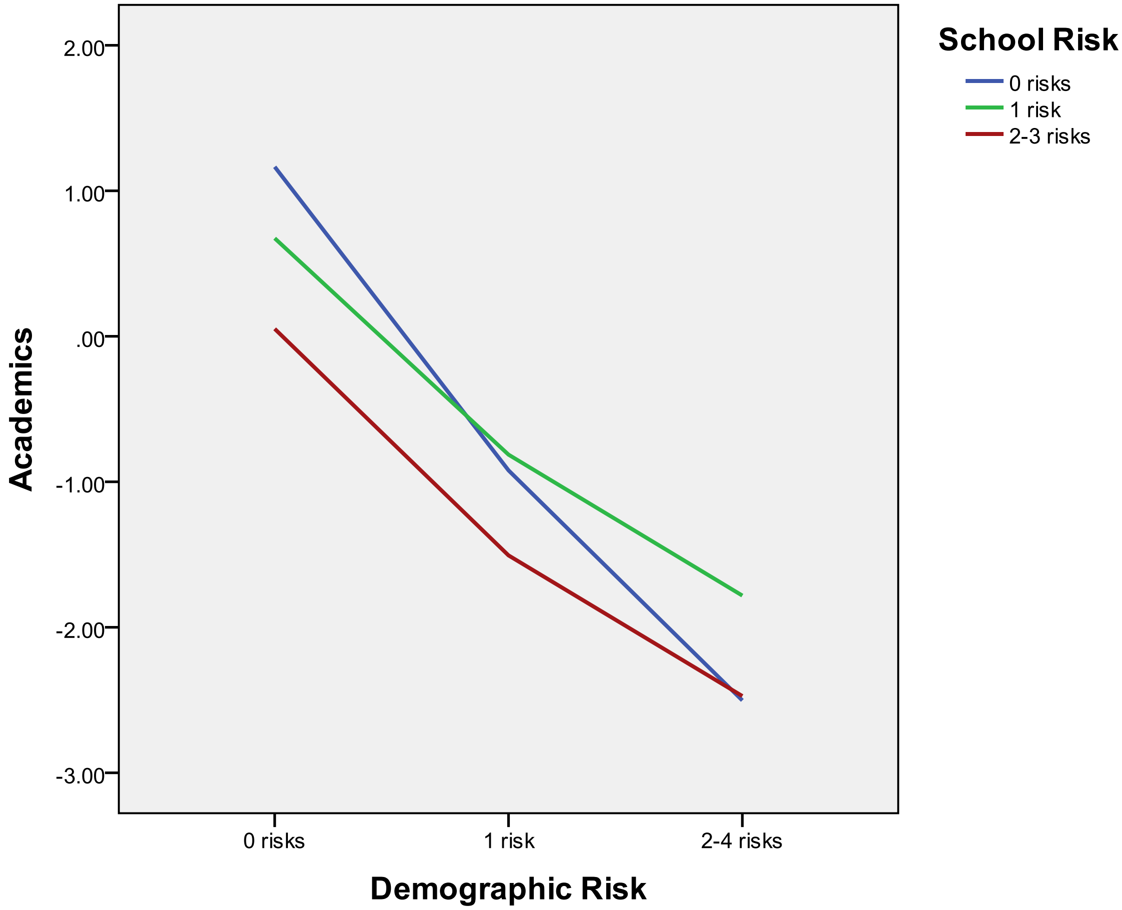

Figure 7. Levels of demographic cumulative risk across levels of school cumulative risk predicting academic outcomes.

Unstandardized regression coefficients for demographic risk at three levels of school risk were calculated. These coefficients increased with increasing levels of school risk (Bs = -1.56, -1.17, -1.02), indicating that the adverse impact of demographic CR on academic outcomes was particularly exacerbated in children with no school risk factors. T-tests confirmed that all of these effects were significant, $t(511) = -11.84$, $t(394) = -7.77$, and $t(170) = -6.07$, respectively.

A similar effect was found for internalizing outcomes. These coefficients decreased with increasing levels of school risk, (Bs = 4.31, 1.53, 0.48), indicating that demographic CR differentially impacts internalizing outcomes across school CR levels. Using the t-test recommended by Jaccard et al (1990) only the first of these effects was significant, $t(511) = 4.18$, $t(394) = 1.77$, $t(170) = .367$, respectively.

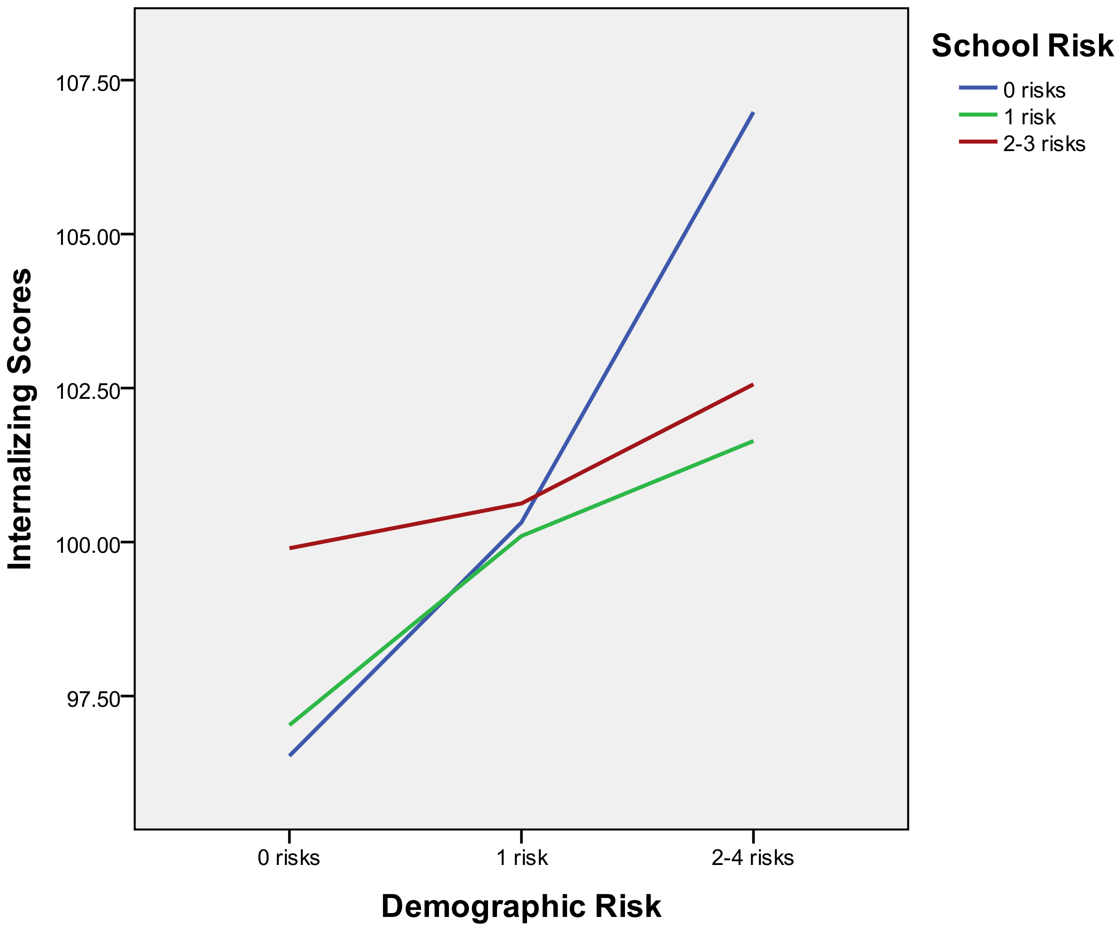

Figure 8. Levels of demographic cumulative risk across levels of school cumulative risk predicting internalizing outcomes.

In addition to two-way interaction effects, several three-way interaction effects were also tested. For each test control variables were entered in the first block of a regression analysis, the three CR domains of interest were entered in the second block, the three two-way interaction effects were entered in the third block, and the three-way interaction term was entered in the final block. I tested all three-way interactions in which demographic CR and school CR were included since these were the only significant two-way interaction effects. None of the three-way interaction effects was statistically significant.

To summarize, nine interaction effects were tested to determine if the level of cumulative risk in one domain of a child's life might differentially impact any of the four possible outcomes when level of CR in another domain was held constant. Since two of these interaction effects were only used to predict academic outcomes, a total of 30 tests were conducted. Two of the 30 possible interaction effects were statistically significant. In particular, demographic CR differentially impacted academic and internalizing outcomes based on the level of school CR.

Interpretation of these effects yields seemingly counterintuitive findings. For example, children with no school risks suffered greater internalizing problems and academic declines than children with any number of school risks.

Structural Equation Modeling: A Measurement Model

In order to test the validity of the proposed domains of risk, a measurement model was fitted in the structural equation modeling program AMOS (Arbuckle, 2010). Structural equation modeling (SEM) is ideal for this type of research question and design for multiple reasons. To begin, the approach permits the creation of latent variables. In this case the risk domains act as latent variables, with each observed variable loading on its proposed domain. Secondly, SEM is capable of correcting for measurement error by providing estimates of error variance parameters (Bryne, 2001). Additionally, AMOS uses a maximum likelihood procedure which utilizes all available data.

The 7 imputed data files from SPSS were used to model 7 unique datasets. AMOS output provides parameter estimates for each of the seven models.

In order to assess the ecological domains CR model, it was compared against a default cumulative risk model which loaded all variables onto one latent variable, aptly named “risk”. This default model is pictured in Figure 9 while the ecological risk model is presented in Figure 10. It should be noted that child race is not a part of this model since it is a categorical variable and not meaningfully interpreted. Each latent variable was scaled by imposing a unit loading identification constraint. The observed variable with the strongest predictive power was used as a reference variable for each latent factor. For each of these reference variables the unstandardized coefficient for the direct effect was fixed to 1.0 (Kline, 2005).

Adequate model fit is determined through a number of indices. A non-significant χ^2 value is among the first criteria used to assess fit. However, because large sample sizes can inflate the χ^2 value, other measures of fit have been adopted. First, a CFI value of .90 or higher is considered a standard measure of good fit. Additionally, an RMSEA value of less than .05 and a 90% confidence interval within the 0 to .1 range are recommended. When comparing two different models it is also essential to look at both AIC values and the change in χ^2. The model with the lower AIC value should be chosen. Additionally, if the model with additional parameters is to be adopted the $\Delta\chi^2$ between models should be significant (Kline, 2005). I incrementally added and deleted paths, assessing fit with each change. The models presented here represent the best fit. All paths are significant unless otherwise noted. Note that error covariances are used to take common observer and common method bias into account (Kline, 2005; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). For example, since the mother reports on household chaos, the error in this measurement is correlated with the error on her reports of relationship quality.

Examining the output listed in Figures 9 and 10 it can be seen that the ecological domain CR model clearly fits the data better than the default model, $\chi^2(1200) = 3648$, CFI = .93, RMSEA = .018 (.017-.018), AIC = 4836.

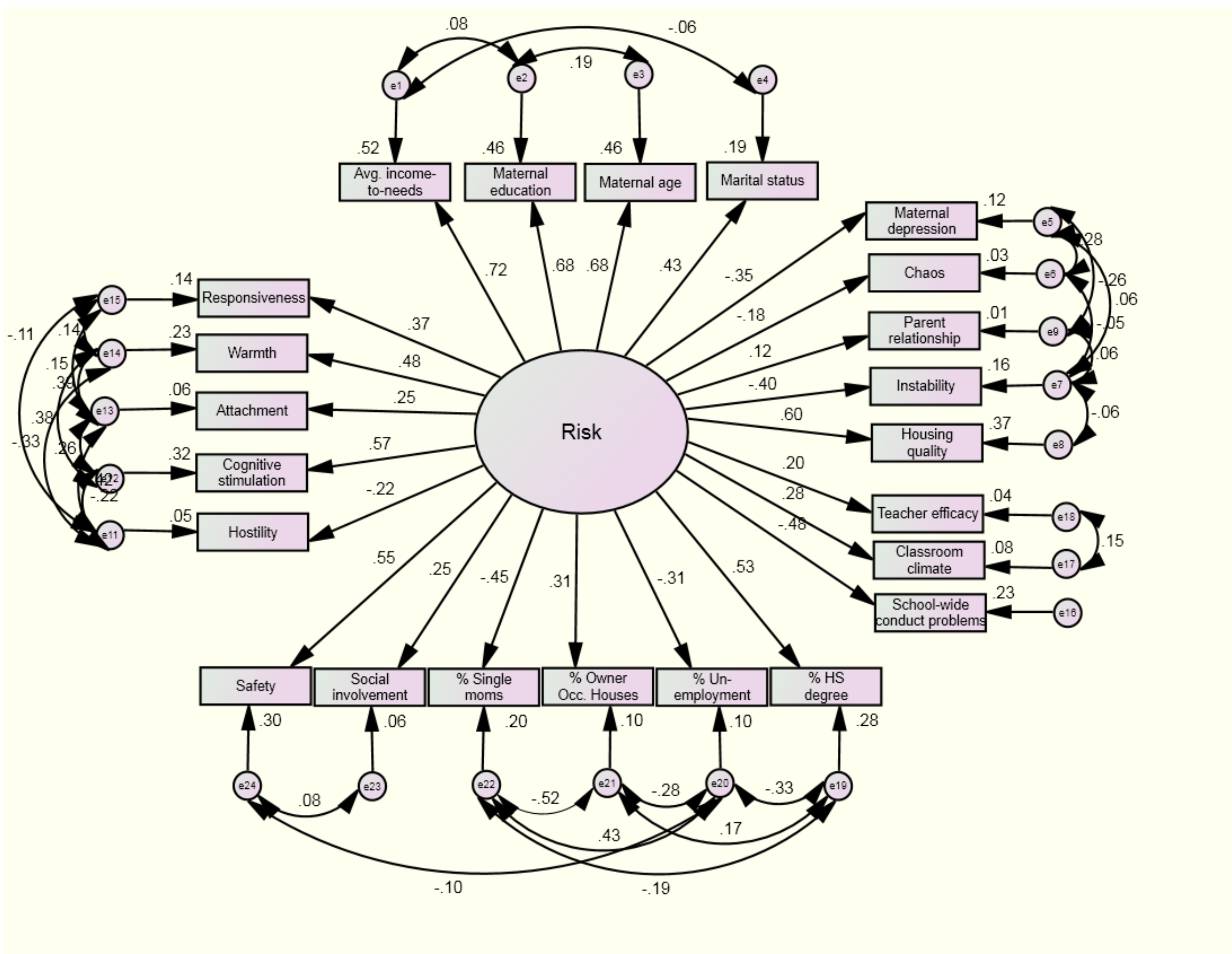

Figure 9. "Lump sum" measurement model of risk factors as measured in AMOS, $\chi^2(1218) = 4190$, CFI = .92, RMSEA = .019 (.019-.020), AIC = 5342. Coefficients are standardized and significant unless otherwise noted.

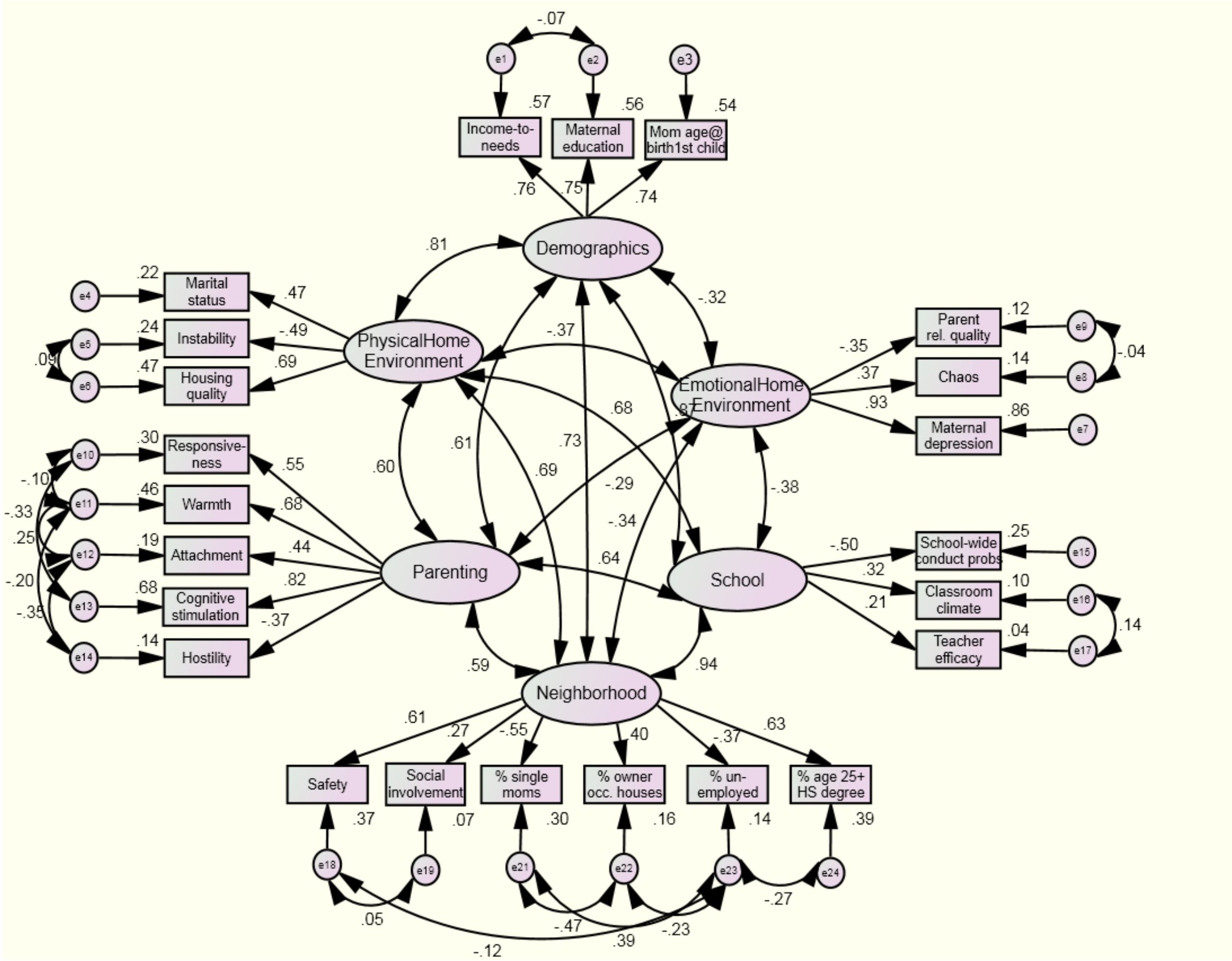

Figure 10. Ecological domains measurement model of risk factors as measured in AMOS, $\chi^2(1200) =$ 3648, CFI = .93, RMSEA = .018 (.017-.018), AIC = 4836. Coefficients are standardized and significant unless otherwise noted.

Structural Equation Modeling: A Mediational Model

In order to test for possible mediation through domains I next created a path model. Because a model using all domains and all outcomes would be far too large for the sample at hand, I focused on a distal and proximal risk domain - demographics and parenting, respectively. I further subdivided the analysis into two models, with one model estimating behavioral outcomes (internalizing and externalizing) and the other model estimating academic and social outcomes. Even with only two risk domains, the full four-outcome model would require fitting more than 110 parameters. Such a model would require a sample size of over 1100 (110 x 10). On the other hand, the largest of the models fitted below estimates approximately 90 parameters.

The direct effect of demographic risk on behavioral outcomes is pictured in Figure 11 while the direct effect of demographic risk on academic and social outcomes is pictured in Figure 12. Figures 11 and 12 confirm that demographic risk significantly predicts academic outcomes, internalizing behaviors, externalizing behaviors, and social outcomes, even when Grade 3 outcomes are also included in the model.

Figures 13 and 14 depict the mediating effect of parenting on these same outcome variables. When parenting is included in the model the relationship between demographic risk and internalizing, externalizing, academic, and social outcomes is reduced. I used guidelines recommended by Cole & Maxwell (2003) to verify mediation. First the mediated model was compared against a number of other possible models in which parameters were incrementally deleted. Tables 7 and 8 provide information on the change in fit in each sequential model, ultimately concluding that Model A (Figure 13) and Model B (Figure 14) are the best fit to the data. Compared to other plausible models, Models A and B have the lowest AIC values.

Besides comparing the fit indices of different models in AMOS, it is possible to estimate meditational effects by examining the total, direct, and indirect effects of a model. Borrowing from Baron and Kenny (1986), Cole & Maxwell (2003) outline four steps that can be used to test for mediation in structural equation modeling. First, the total effect of X on Y should be determined. Next, the overall indirect effect of X on Y through M (mediator) provides an estimate of the degree to which M mediates the relationship. The indirect effect is that part of the total effect of X on Y that would disappear if M were controlled for. Thirdly, the overall direct effect should be estimated. The overall direct effect is that part of the total effect of X on

Y that is not mediated by M. Lastly, tests of statistical significance should be conducted. Table 9 presents the total, direct, and indirect effects for the mediation models. Clearly, parenting reduces the direct effect of demographic risk on all outcomes.

The best means of conducting statistical significance tests with structural equation models is to determine if $ab = 0$. (a being the path from X →M; b being the path from M →Y). The product of a and b can be tested directly by using the equation put forth by Sobel (1982) and calculating a z-statistic (Preacher & Leonardelli, 2003).

I used the Sobel equation to generate a test statistic for each ab combination. This statistic was significant in all cases, verifying the meditational effect of parenting on all outcomes, academics: $z = 4.69$, $p < .01$; internalizing: $z = -2.81$, $p < .01$; externalizing: $z = -5.64$, $p < .01$; social: $z = 5.29$, $p < .01$. In combination, these results indicate that parenting risk partially mediates the relationship between demographic risk and all four outcomes.

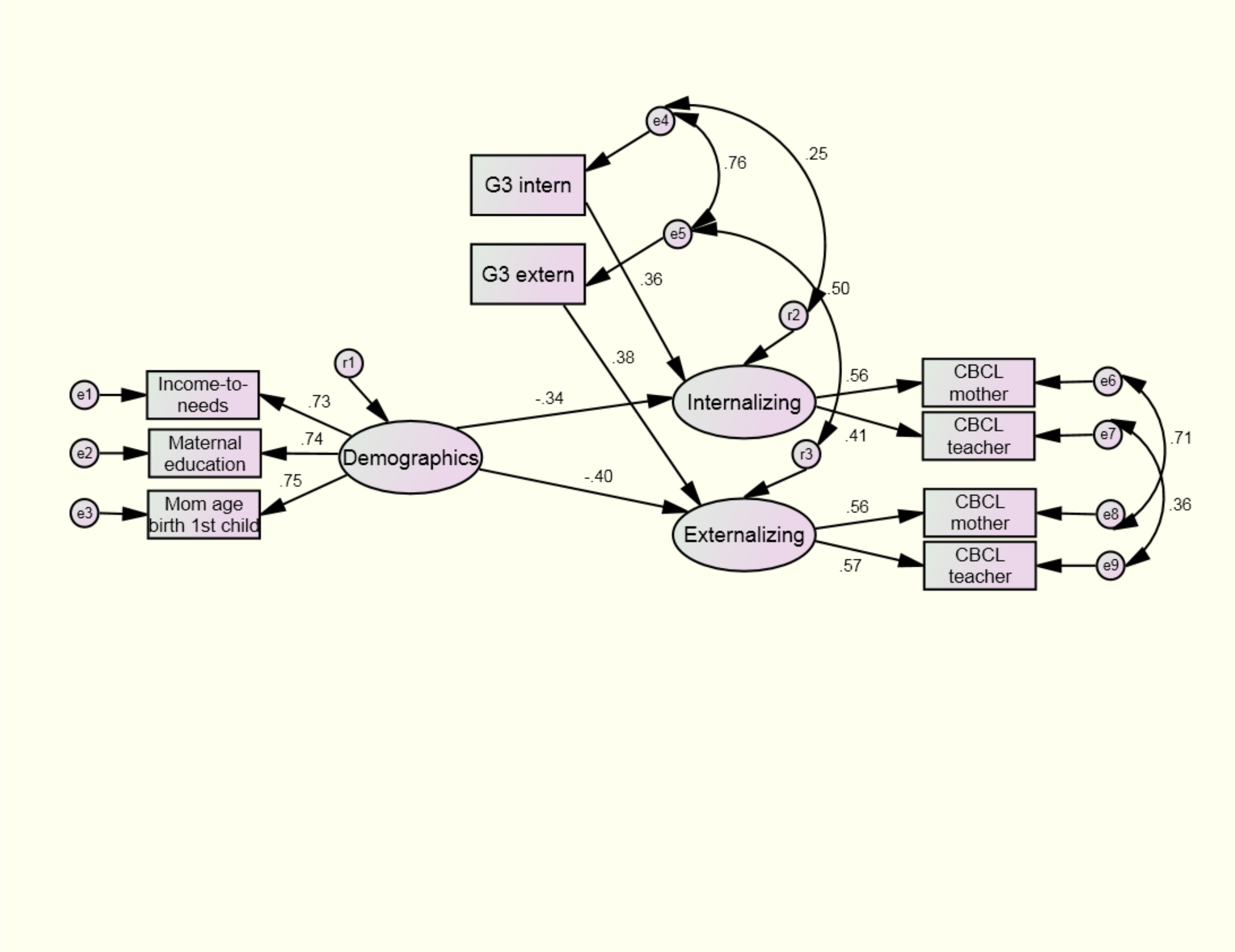

Figure 11. Path model of demographic risk predicting internalizing and externalizing behaviors, $\chi^2(120) = 525.01$, CFI = .98, RMSEA = .023 (.021-.025), AIC = 933. Coefficients are standardized and significant unless pictured in bold italics.

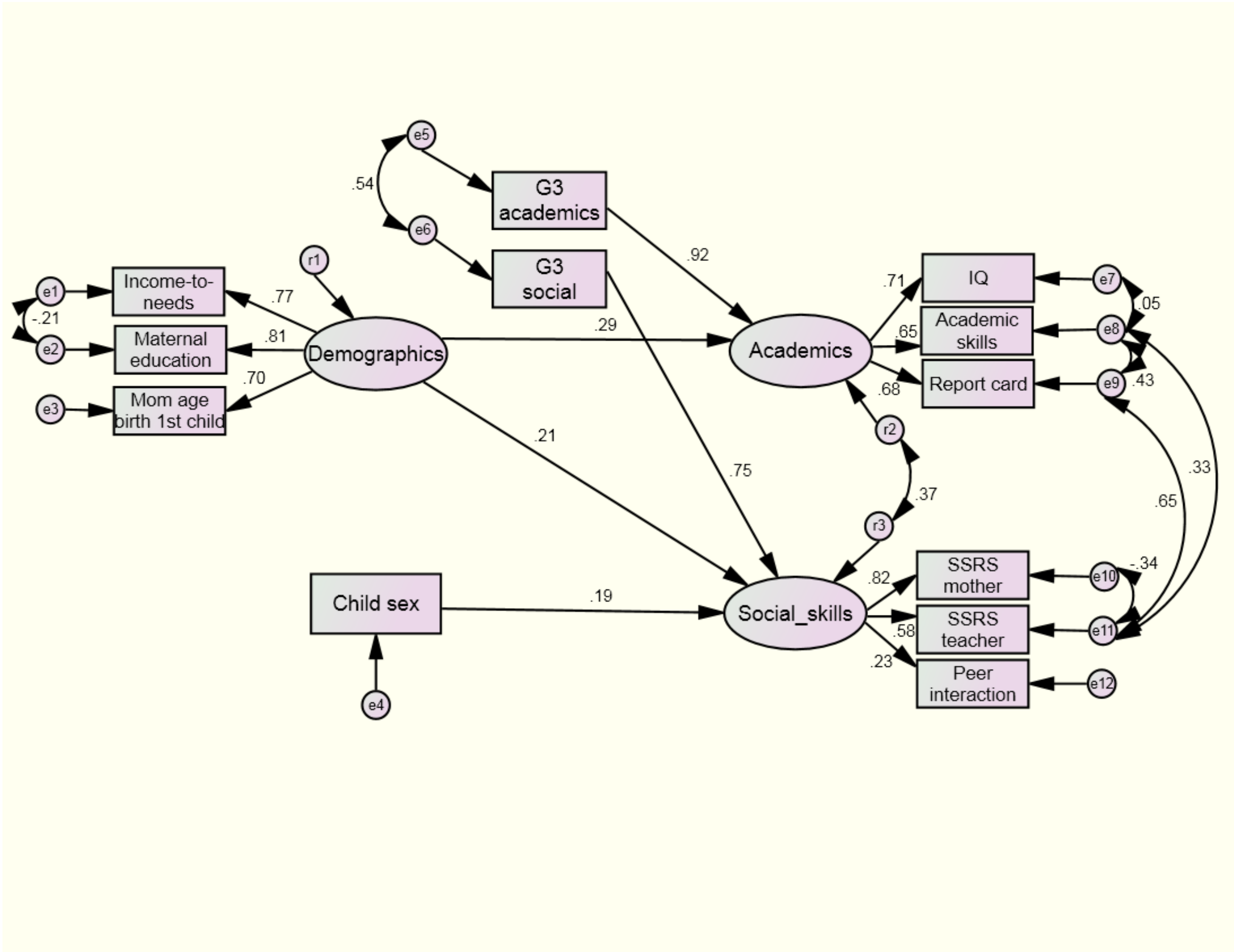

Figure 12. Path model of demographic risk predicting academic and social outcomes, $\chi^2(264) = 3238.02$, CFI = .92, RMSEA = .042 (.040-.043), AIC = 3790. Coefficients are standardized and significant unless pictured in bold italics.

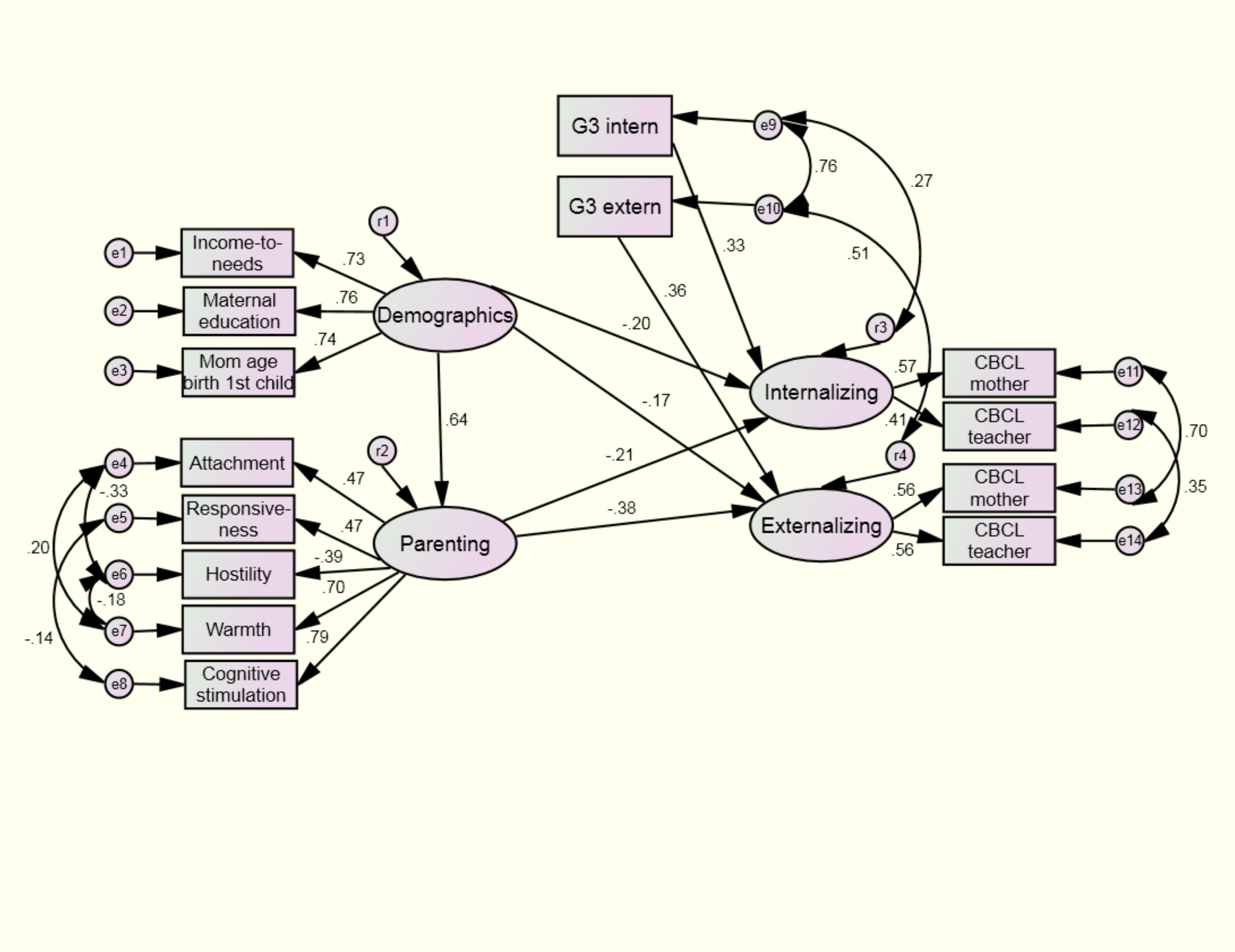

Figure 13. Mediational model of ecological risk (Model A). Parenting partially mediates the relationship between demographic risk and internalizing and externalizing behaviors, $\chi^2(378) = 2400.36$, CFI = .94, RMSEA = .029 (.028-.030), AIC = 3072. Coefficients are standardized and significant unless pictured in bold italics.

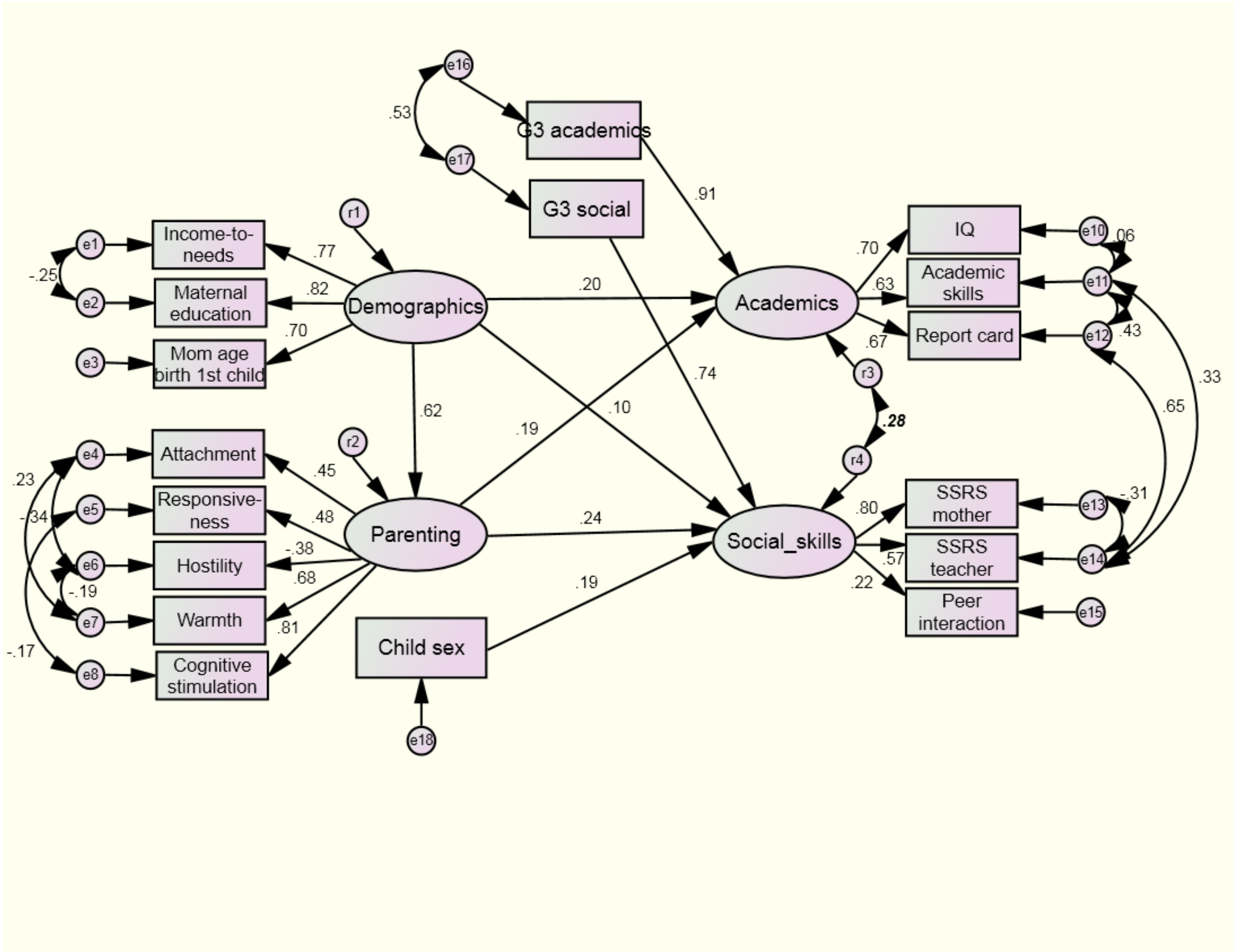

Figure 14. Mediational model of ecological risk (Model B). Parenting partially mediates the relationship between demographic risk and academic and social outcomes, $\chi^2(612) = 5950.79$, CFI = .89, RMSEA = .037 (.036-.038), AIC = 6767. Coefficients are standardized and significant unless pictured in bold italics.

Table 7

Change in Fit Indices when Estimating Different Mediational Models of Parenting on the Relationship between Demographic Risk and Behavioral Outcomes

Model	χ^2	**Df**	**CFI**	**RMSEA (90 % CI)**	**AIC**
Model A	2400	378	.94	.029 (.028-.030)	3072
delete Demographic → Internalizing[na]	2465	384	.94	.029 (.028-.030)	3125
delete Demographic → Externalizing[na]	2459	384	.94	.029 (.028-.030)	3119
delete Demographic → Parenting[na]	4575	384	.87	.041 (.040-.042)	5235

Note. na = change not accepted because deletion of path does not improve model fit

Table 8

Change in Fit Indices when Estimating Different Mediational Models of Parenting on the Relationship between Demographic Risk and Academic and Social Outcomes

Model	χ^2	**Df**	**CFI**	**RMSEA (90 % CI)**	**AIC**
Model B	5951	612	.89	.037 (.036-.038)	6767
delete Demographic →Academics[na]	6135	618	.88	.037 (.036-.038)	6939
delete Demographic → Social[na]	6002	618	.89	.037 (.036-.038)	6806
delete Demographic → Parenting[na]	7807	618	.85	.042 (.042-.043)	8611

Note. na = change not accepted because deletion of path does not improve model fit

Table 9

Total, Direct, and Indirect Effects of Demographic Risk on Academic, Internalizing, Externalizing, and Social Outcomes

Relationship	Total Effect	Direct Effect	Indirect Effect
Demographic → Academics	.693	.388	.305
Demographic → Internalizing	-.335	-.114	-.221
Demographic → Externalizing	-.550	-.121	-.429
Demographic → Social	.641	.137	.504

Since the structural equation model capitalizes on the continuous nature of risk variables, I tested this same mediation model in SPSS using the cumulative risk domains. In other words, I tested the degree to which the number of parenting risks might mediate the relationship between the number of demographic risks and all outcome variables. Demographic CR was a significant predictor of academic, internalizing, externalizing, and social outcomes after controlling for prior outcomes and child gender: $t(1077) = -8.15$, $p < .01$; $t(1077) = 4.03$, $p < .01$; $t(1077) = 10.00$, $p < .01$; $t(1077) = -6.46$, $p < .01$. Additionally, demographic CR was a significant predictor of parenting CR, $t(1077) = 11.60$, $p < .01$. When both demographic CR and parenting CR were entered into a regression model, parenting retained its significant effect on all outcomes, $t(1077) = -3.33$, $p < .01$; $t(1077) = 3.08$, $p < .01$; $t(1077) = 8.10$, $p < .01$; $t(1077) = -5.39$, $p < .01$. Using Sobel's equation I tested the product of paths *a* and *b* in each instance. All four tests indicated mediation was at play, $z = -3.23$, $p < .01$; $z = 2.98$, $p < .01$; $z = 6.64$, $p < .01$; $z = -4.90$, $p < .01$.

In summary, both the latent variable and ecological domain CR model support the meditational effect of parenting risk on all outcome variables.

DISCUSSION

Using the NICHD Study of Early Childcare and Youth Development, I examined cognitive, behavioral, and socio-emotional sequelae of multiple risks from birth through 4rd grade. Using both theoretical and empirical criteria I divided the 24 risk factors into 6 domains – demographics, physical home environment, emotional home environment, parenting, school, and neighborhood. These domains were then used to predict academic, behavioral, and social outcomes for the same children in 4th grade after controlling for prior outcome levels at 3rd grade.

Factor analysis was used to determine if the 24 risk factors would benefit from added structure. Initial tests confirmed that approximately 85% of the variance could be accounted for by an underlying factor structure. This structure was not exactly as predicted however. While the demographic, parenting, school, and neighborhood domains were rather easily identified, the home environment factor was more difficult. It was determined that home environment was best sub-divided into two domains, one representing structural or physical components of the home and the other representing emotional components of the home. It may seem counterintuitive that chaos loaded on the emotional domain while instability loaded on the physical domain. However, upon further inspection this in fact makes theoretical sense and is a worthwhile finding in itself. Chaos measures the degree to which predictability and routine are experienced on a daily basis. On the other hand, instability measures the total number of residential moves, school/daycare changes, and changes in household composition throughout the child's lifetime. The latter are all physical forms of instability while the former could be thought to affect the child at a more personal and emotional level.

In order to create a CR model, all variables were dichotomized according to either theoretical or statistical criteria. As an example of theoretically-based cut-offs, the NICHD SECCYD advises that poverty be defined as an income-to-needs ratio of 2.0 or less (ICPSR, 2010). When no theoretical criteria were available, the dichotomization rules were based on an upper (or lower) quartile cut-off. Each child was therefore assigned either a 0 (or risk) or 1 (risk) for each of the 24 variables.

In order to determine if a single variable carried the weight of each CR domain score I used hierarchical regression to examine the influence of domain CR and the continuously-measured variables which contributed to that domain. One variable, maternal depression, presented problems on all but one outcome variable. When entered into a hierarchical regression model with emotional home CR, the domain variable was no longer significantly predictive of any outcome variables except externalizing problems. Further analyses confirmed that, after controlling for main effects, maternal depression x emotional home environment CR significantly predicted internalizing behaviors, $t(1077) = -2.01$, $p < .05$. When mothers were not depressed, children at moderate and high levels of home risk did not differ much in their internalizing scores. However, when mothers were depressed the children with high levels of risk suffered much more from internalizing problems. Despite the finding, when maternal depression CR was deleted from the emotional home CR domain results were not greatly altered. A future step would be to use this interaction effect in place of the emotional home CR index for the hierarchical regression model. As an even more precise measurement of emotional home environment risk, I anticipate that such a model would explain even further variance in the outcomes.

The impact of maternal depression highlights the importance of using control checks to determine the relationships between both individual variables and their domains. Maternal depression is often used as a control in child development research. Although this is a tempting means of dealing with questionable risk factor, the results here suggest that in at least some cases maternal depression may moderate the relationship between cumulative risk and developmental outcomes. Researchers must be aware of these types of relationships when creating CR indices.

With a valid base model built, I next turned my efforts to testing the Ecological Domains approach against a traditional/total CR model. These two types of CR models were tested for their ability to predict academic, behavioral, and social outcomes after controlling for gender and prior levels of these same outcome variables. The traditional CR approach used the total number of risks a child experienced as an independent variable. Total risk was defined as the sum of all dichotomized variables across domains. The second model, referred to as the Ecological Cumulative Risk approach, used the six domains to predict the same outcomes. Both risk models were estimated with multiple linear regression.

On average, the ecological domains model explained 1% more variance in the outcome variables than the total CR model, suggesting that domains were only a slightly better means of modeling risk than a lump sum approach. I took the comparison between models a step further by examining if it were possible for the total number of risks to carry more weight, even after the influence of domains was considered. I used hierarchical linear regression, entering control variables in the first block, the six ecological CR domains in the second block, and total CR in the third block. After controlling for CR in each domain, total CR was not a significant predictor of academic, internalizing, or social outcomes. However, it did significantly predict externalizing outcomes.

The results above provide a number of insights. For one, an ecological domains approach to modeling cumulative risk explains a negligible amount of additional variance than a total CR metric. Furthermore, the influence of within-domain risk and total risk varies according to the outcome measured. After controlling for CR in other domains, as well as total CR, parenting risk was a significant predictor of social outcomes. However, total CR was the only significant predictor of externalizing outcomes; none of the domain specific CR scores added significant variance to the model after controlling for total amount of CR. One of the major criticisms of CR models is that they do not provide enough information for targeting the mechanisms through which developmental outcomes are impinged (Whipple, 2010). These results indicate that not all risks affect all outcomes equally. In some instances the domain is a crucial indicator for an outcome; in other cases total amount of risk is more important.

One of the major drawbacks of traditional CR models is their assumption of additivity, which prohibits variables from interacting. A central reason for identifying domains of risk was to determine if interaction effects might exist between these domains. By generating more than just a total CR metric it was possible to create interaction terms across domains. I focused particularly on the interaction between a distal domain, demographics, and the microsystem domains. Using linear regression, the two CR domain variables of interest (i.e. demographic CR and school CR) were entered in one block of the equation while the interaction term was entered in a subsequent block (demographic CR x school CR). These analyses provided some evidence for interaction effects. However, the interpretation of these effects is somewhat counterintuitive.

Take, for example, the significant interaction between demographic CR and school CR. Children with no school risks suffered greater internalizing problems and academic declines than children with any number of school risks. This finding is contrary to the hypothesis that at similar levels of risk in one domain, children would experience worse outcomes when inundated with higher levels of risk in a second domain. It does not appear that these findings can be attributed to a floor effect. Children experiencing moderate and high-level school CR are not at low levels of academic competence or high levels of internalizing problems when demographic risk is at a minimum. Rather, the interpretation of these effects might be more social in nature.

In the aggregate these results resemble findings from the Moving to Opportunity Study in which the children of families who received vouchers to move into a better neighborhood actually fared worse in the short-term (Rosenbaum & Harris, 2000). Researchers caution that the Moving to Opportunity results should be interpreted cautiously since only a small portion of the study members moved into better neighborhoods. The same caution is warranted here; out of the 1078 cases only 136 fell into the high-risk (2 or more risks) school category. Further research is needed to confirm if these interaction effects are a result of sample demographics or if results are in fact valid. Unfortunately, it is unlikely that an uneducated, poor, young mother would settle in a high quality neighborhood with a good school. However, if the findings are valid it is entirely possible that a social comparison mechanism could be at play such that children in no risk schools suffer when demographic characteristics within the home are not on par with those of their peers. Further studies are warranted before making any definitive conclusions, particularly since school-level data are difficult to collect.

Since statistically significant two-way interaction effects were detected I also tested the possibility of three-way interactions between the ecological risk domains. None of these added significant variance to their respective models.

As mentioned throughout this paper, a strong advantage of CR is that multiple risks can be modeled with small sample sizes. However, since NICHD SECCYD is a large, national sample I used this to my advantage by verifying my initial analyses with structural equation modeling. SEM confirmed that the ecological domains model fit the data better than a total risk/lump sum model. Additionally, path analyses were used to test for the possibility of mediation. As a distal risk domain in both proximity to the child and time, demographics was used to predict parenting risk and outcomes. The best-fitting model indicated a meditational role for parenting on all outcomes. Follow-up mediation tests in SPSS using the cumulative risk domains supported these same results. This is particularly notable since CR inherently reduces the variability of individual risk factors. The fact that total amount of risk in a more distal domain was mediated by total amount of risk in a proximal domain supports, 1- the creation of domain-specific CR indices, 2-the use of Bronfenbrenner's theory to guide analyses examining the means by which risk influences the child.

This study provides a number of insights with regard to cumulative risk. First, results support the use of ecological domains when modeling risk. Factor analysis confirmed the existence of more than one underlying component and structural equation modeling verified this. Each domain predicted outcomes to a variable degree. As expected, the most proximal domain to the child, parenting, was the strongest predictor. Parenting CR significantly predicted academic, internalizing, externalizing, and social outcomes even after controlling for the effects of other domains.

Secondly, an additive measurement model of risk was generally supported. Only two of 30 two-way interaction effects were statistically significant. Using the Bonferroni correction procedure (Bland & Altman, 1995), the adjusted p value for 30 comparisons at α =.05 is 0.002. Overall, the lack of interaction effects suggests an additive model of risk fits that data better than a multiplicative measurement model.

Next, the path model estimated in this study suggests that mediation of risk domains is present. This finding is in line with Bronfenbrenner's bioecological model of development which posits that children are affected by multiple contexts, each at a varying degree of proximity. In this case the effects of demographic risk were at least partially mediated by parenting risk. I cannot yet conclude how prevalent this type of domain mediation is since only demographic and parenting CR were examined. I chose to focus on these two risk domains for good reason. First, demographic risk was the most distal to the child in both space and time. Most demographic variables (i.e. mother's age at birth of first child, maternal education) influenced children well before the 3rd grade parenting measures. Arguably, these structural conditions did not directly affect the child. On the other hand, amount of risk experienced in the parenting domain was the strongest predictor of all outcome measures. Therefore, the meditational role of parenting between demographic CR and outcomes is likely one of the strongest. There may be no such relationship between parenting and school or demographics and neighborhood.

Taken together these findings provide mixed support for the incorporation of an Ecological Domains Cumulative Risk Model in future studies. The domains explained more variance in all outcomes than the total (or lump sum) CR model alone. However, the additional variance explained is negligible (.5-1%). Although the SEM analyses used the continuous risk variables, the domain model was clearly supported. Domains may be important for a number of reasons. To begin, they address at least four of the disadvantages of traditional CR models. Although risks are not weighted as in the traditional CR technique, the categorization of risk variables allows for increased variability in the data. Next, by categorizing risks the variables are not all considered equal; naturally, differentiation is necessary for classification. The ecological approach also allows for better determination of variables by testing how well each risk loads on a domain. Perhaps most importantly, the domain approach allows for more than one CR metric to be created. As a result it is possible to examine the possibility of both moderator and mediator effects of domains. By continuing in this direction we may be able to address a major criticism of CR methodology, namely the inability to specify intervention strategies. If meditational processes can be identified, it becomes more possible to determine the mechanisms at play and to develop effective interventions.

Although the current study did not provide support for the multiplicative nature of risk variables, analyses suggest that risk domains are not entirely independent. For example, child race loaded most highly on the neighborhood factor while neighborhood social involvement loaded best on physical home environment (see Table 3). I retained these variables on their originally hypothesized domains due to theoretical support. However, the fact that race is correlated with neighborhood characteristics implies some degree of overlap between risk domains. Further exploration of meditational models would begin to tease apart these relationships by determining what degree distal risks can be explained by more proximal processes.

In summary, this research provides mixed results. The implicit assumption of CR models, that risk is additive, was generally supported. Far fewer interaction effects were significant than hypothesized. Furthermore, the fact that externalizing behaviors were predicted by total CR, even after controlling for domain specific CR, suggests that an additive CR metric warrants continued attention. The decision of using CR domains versus traditional/total CR should be determined based on the risks and outcomes examined. Not all studies can easily create two or more risk domains. In these instances total CR is more beneficial than an arbitrarily defined ecology. Domains may be more important for specific outcomes (i.e. grade retention, emotional regulation, health conditions), whereas total amount of risk may be a better generic predictor of developmental conditions. Perhaps total CR best predicts overall externalizing problems but a domain-specific CR approach would better predict oppositional defiant disorder. Clearly, the role of risk domains versus total risk warrants more attention in future research.

Limitations

Despite addressing a major limitation of cumulative risk research, this study suffers from its own drawbacks. The arbitrariness of risk cut-offs (i.e. highest or lowest quartile) is still a valid concern. Where possible, clinically-defined cut-offs were used; for example, risk for maternal depression was defined by a score of 16 or greater on the CES-D. Unfortunately such criteria do not exist for most measures. A future step for researchers in this field is to better define risk cut-offs. One means of doing this is to use nationally representative data to determine the level at which certain variables impinge upon developmental outcomes.

Prior to beginning this research I considered several other studies but settled on NICHD SECCYD for its multi-method, multi-observer data collection procedures and wide array of potential risk variables. Nevertheless, as with any longitudinal study, NICHD SECCYD suffers from attrition, limited sample demographics, selection bias, and imprecise measures.

Attrition analyses confirmed that children who dropped out of the study came from lower income families. Since income is closely related to a constellation of other risk factors, attrition could bias the results of this study. As mentioned previously this was not a high risk sample from the start. For one, researchers did not enter or collect data in neighborhoods that were considered unsafe (B. Knoke, personal communication, August 4, 2010). This fact coupled with attrition findings likely underestimates the degree of risk with respect to the general population.

A significant appeal of this study was the multi-method, multi-observer data collection technique. Parents, teachers, principals, caregivers, and study children themselves were administered questionnaires and experimental protocol. However, due to the difficulty of ascertaining questionnaires from these added reporters, about 15% of school variable data were missing. This was after the deletion of 257 cases that did not have data past 1 year and 29 additional cases that were dropped. I used *t* tests to assess whether children who had missing data on school-level variables differed from their peers on outcome scores. Children with missing and non-missing school data did not significantly differ on any of the outcomes: academics, $t(1040) = -1.02$, $p = .31$; internalizing, $t(1046) = -.69$, $p = .49$; externalizing, $t(1046) = -.77$, $p = .44$; social, $t(1048) = .14$, $p = .89$. Despite this, other statistics suggest that, as a whole, children in this study attended relatively low risk schools. In 2008-2009 approximately 22% of elementary-aged children attended high poverty schools, defined as schools in which 75% or more children qualify for the free and reduced price lunch program (Aud et al., 2011). Less than 6% of this sample falls into the high poverty school group.

Selection bias is another shortcoming of this research. The sample, which began as predominantly middle class Caucasian families, was even more inclined in that direction by the time children were in 4th grade. This may downwardly bias the effects of risk, particularly given the tendency for low income and minority children to experience higher levels of risk (Evans, 2004). By further subdividing variables into domains, the effects of risk were likely even further underestimated compared the general population. It is possible that many of the moderator effects did not reach statistical significance due to a smaller proportion of children in the high risk category of certain domains.

Another limitation with secondary data is that researchers must make do with the measures at hand. Although NICHD SECCYD is incredibly comprehensive, the tradeoff with secondary data is that some measures are not as targeted as one might like. This was particularly the case for school and home environment variables. Ideally I would have used a measure of school structural quality, class size, abuse/violence within the home, parental criminality, and parental expectations for the child. Although I chose theoretically-supported measures as risk factors, some of these variables were measured more precisely than others. For example, quality of mother's relationship was based on only one variable while quality of the home environment was based on the aggregation of three variables.

A central purpose of studying risk in children is to identify stressors and intervene in order to reduce the likelihood of developing maladaptive outcomes. Although theoretically interesting, on a practical level interaction effects make it more difficult to predict the consequences of changing the value of a variable. As a result, interaction effects between variables make intervention efforts even more difficult. In this case, when moderation was detected it did not always work as predicted. Children at high risk across domains were not necessarily those who could benefit most from intervention efforts. The interaction effect between demographic CR and school CR indicated that children who experience no school risk but high demographic risk are more prone to problems. Despite its simplistic manner, perhaps the best advice to interventionists and policy makers is to limit the number of risks children experience in all domains.

Future Directions

Future studies would benefit from narrowing in on more risk variables that fit into these domains. In particular, the differentiation between physical and emotional home environment domains warrants more investigation. Controlling for other CR domains, academic outcomes were significantly predicted by emotional home environment but not by physical home environment. Additional variables that might be considered are violence within the home, overall household composition, and changes in parents' work schedules.

In addition to these six domains, health or biological risk status could also be incorporated in a domain model. This domain approach could be applied to different age groups such that the influence of risk status on both younger and older children could be understood. For example, a daycare/care giving domain could easily be substituted for the school domain in young children. On the other hand, neighborhood may garner greater interest as children get older.

The generalizability of these findings is still questionable. The NICHD Study of Early Child Care and Youth Development is not a nationally representative sample and likely underestimates risk compared to the general population. This same model should be applied to other age and demographic groups (i.e. high risk) to determine its applicability across human development. Because data collection is costly in both time and money, I encourage researchers to explore secondary datasets like NICHD SECCYD. Learning to navigate these large-scale, longitudinal studies can be difficult, but the data are incredibly rich and worthwhile.

Future studies should take further advantage of this dataset by using multi-level modeling approaches to examine the trajectory of risk over time.

Conclusions

Using the NICHD Study of Early Child Care and Youth Development I created a multi-domain ecological risk model to challenge the additive assumption implicit to cumulative risk. I utilized the strengths of traditional CR models along with the advantages of multiplicative models to measure multiple risks. The approach was guided by Bronfenbrenner's bioecological model of development which posits that the relationships between multiple settings must be considered in order to gain a full understanding of child development.

The current study highlights the importance of understanding the underlying relationships between variables. Whether aware of it or not, when choosing a measurement model researchers make assumptions about the nature and distribution of variables. At the very least variables should be checked for possible interactions with the total CR metric. If one variable within a CR index carries the majority of predictive power or alters the effect of the remaining variables it should be approached cautiously. Such was the case with maternal depression in this study.

Previous research has found that moderator effects exist in both continuous and cumulative risk models (Ackerman et al., 1999; Brennan et al., 2003; Mrug et al., 2008; Pungello et al.,1996; Whipple et al., 2010). Such findings were generally not supported in this study. A somewhat new area of research approached here was the mediation of risk through domains. Multi-level modeling approaches would be especially helpful for teasing apart the effects of distal risk domains on more proximal domains after controlling for previous levels of the outcome variable. Such analyses could inform research into a risk trajectory model. For example, if demographic risk is largely mediated through parenting then parenting courses may be a fruitful avenue for intervention. A central goal for researchers and policymakers alike would be to determine the most cost-effective and powerful domain to target.

To summarize, the Ecological Cumulative Risk Model is essentially a cumulative risk approach but with a multiplicative measurement component. As such, it claims the advantages of cumulative risk in that even studies with small sample sizes can benefit from the measurement technique. Ecological CR also reduces the limitations of traditional CR models by allowing for the examination of moderation and mediation through various domains of risk. The model was supported but warrants further investigation with diverse samples.

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APPENDIX

Results of all Two-Way Interaction Effects Tested

Interaction Effect	**Outcome**	**Variable Entry**	**Unst. B**	**Std. Error**	***t* value**	***p* value**
Demographics x Physical Home	Academics	Constant	0.75	0.36	2.09	.038
		Child Sex	0.15	0.10	1.55	.122
		G3 Academics	0.76	0.02	37.82	.000
		Demographics	-0.56	0.23	-2.46	.015
		Physical Home	-0.10	0.16	-0.62	.533
		Demo x Phys Home	0.02	0.09	0.20	.839
	Internalizing	Constant	71.19	3.87	18.41	.000
		G3 Internalizing	0.24	0.02	11.16	.000
		Demographics	2.35	2.10	1.12	.263
		Physical Home	0.59	1.60	0.37	.713
		Demo x Phys Home	0.07	0.93	0.08	.938
	Externalizing	Constant	58.52	3.38	17.33	.000
		G3 Externalizing	0.33	0.02	17.58	.000
		Demographics	2.42	1.99	1.22	.226
		Physical Home	2.00	1.38	1.46	.147
		Demo x Phys Home	0.48	0.83	0.57	.570
	Social	Constant	-0.79	0.37	-2.18	.030
		Child Sex	0.88	0.10	9.16	.000
		G3 Social	0.79	0.03	23.19	.000
		Demographics	-0.09	0.24	-0.39	.697
		Physical Home	-0.05	0.17	-0.30	.768
		Demo x Phys Home	-0.10	0.10	-0.97	.334

Interaction Effect	Outcome	Variable Entry	Unst. B	Std. Error	*t* value	*p* value
Demographics x Emotional Home	Academics	Constant	0.89	0.28	3.16	.002
		Child Sex	0.15	0.10	1.63	.105
		G3 Academics	0.75	0.02	37.97	.000
		Demographics	-0.60	0.15	-4.06	.000
		Emotional Home	-0.18	0.14	-1.29	.196
		Demo x Emot Home	0.03	0.08	0.40	.693
	Internalizing	Constant				
		G3 Internalizing	68.65	3.24	21.18	.000
		Demographics	0.24	0.02	11.00	.000
		Emotional Home	2.39	1.61	1.48	.142
		Demo x Emot Home	2.68	1.49	1.80	.075
			0.10	0.85	0.12	.906
	Externalizing	Constant				
		G3 Externalizing				
		Demographics	55.46	2.85	19.45	.000
		Emotional Home	0.32	0.02	17.20	.000
		Demo x Emot Home	5.00	1.41	3.54	.001
			3.30	1.31	2.51	.013
	Social	Constant	-0.14	0.75	-0.19	.850
		Child Sex				
		G3 Social				
		Demographics	-0.59	0.32	-1.84	.068
		Emotional Home	0.88	0.10	9.21	.000
		Demo x Emot Home	0.79	0.04	22.27	.000
			-0.36	0.16	-2.19	.030
			-0.07	0.16	-0.41	.686
			-0.03	0.09	-0.38	.706

Interaction Effect	**Outcome**	**Variable Entry**	**Unst. B**	**Std. Error**	***t* value**	***p* value**
Demographics x Parenting	Academics	Constant	0.97	0.32	3.04	.003
		Child Sex	0.14	0.10	1.43	.153
		G3 Academics	0.74	0.02	36.21	.000
		Demographics	-0.54	0.17	-3.15	.002
		Parenting	-0.23	0.15	-1.51	.130
		Demo x Parenting	0.01	0.08	0.16	.877
	Internalizing	Constant	74.31	3.35	22.20	.000
		G3 Internalizing	0.24	0.02	11.01	.000
		Demographics	-0.46	1.82	-0.26	.799
		Parenting	-0.73	1.56	-0.47	.639
		Demo x Parenting	1.57	0.85	1.84	.067
	Externalizing	Constant G3	56.90	3.03	18.78	.000
		Externalizing	0.30	0.02	16.38	.000
		Demographics	2.89	1.58	1.83	.069
		Parenting	4.25	1.43	2.97	.003
		Demo x Parenting	0.50	0.80	0.63	.533
		Constant	-0.33	0.35	-0.96	.340
		Child Sex	0.84	0.10	8.84	.000
	Social	G3 Social	0.72	0.04	20.50	.000
		Demographics	-0.11	0.19	-0.57	.567
		Parenting	-0.25	0.17	-1.45	.149
		Demo x Parenting	-0.13	0.10	-1.31	.194

Interaction Effect	**Outcome**	**Variable Entry**	**Unst. B**	**Std. Error**	***t* value**	***p* value**
Demographics x School	Academics	Constant	1.48	0.31	4.80	.000
		Child Sex	0.15	0.09	1.56	.120
		G3 Academics	0.75	0.02	37.99	.000
		Demographics	-1.02	0.18	-5.63	.000
		School	-0.50	0.15	-3.27	.001
		Demo x School	0.26	0.09	2.87	.006
	Internalizing	Constant	65.79	3.27	20.10	.000
		G3 Internalizing	0.25	0.02	11.34	.000
		Demographics	6.39	1.72	3.71	.000
		School	3.27	1.44	2.27	.024
		Demo x School	-1.88	0.84	-2.25	.027
	Externalizing	Constant	54.94	3.11	17.69	.000
		G3 Externalizing	0.33	0.02	17.61	.000
		Demographics	5.84	1.61	3.62	.001
		School	3.06	1.36	2.25	.026
		Demo x School	-0.65	0.80	-0.81	.421
	Social	Constant	-0.70	0.34	-2.03	.043
		Child Sex	0.88	0.10	9.17	.000
		G3 Social	0.80	0.03	23.18	.000
		Demographics	-0.33	0.19	-1.75	.082
		School	-0.01	0.17	-0.06	.956
		Demo x School	-0.04	0.09	-0.43	.671

Interaction Effect	Outcome	Variable Entry	Unst. B	Std. Error	*t* value	*p* value
Demographics x Neighborhood	Academics	Constant	0.73	0.34	2.12	.034
		Child Sex	0.15	0.09	1.53	.127
		G3 Academics	0.75	0.02	38.08	.000
		Demographics	-0.34	0.20	-1.66	.099
		Neighborhood	-0.14	0.16	-0.87	.385
		Demo x Neighborhood	-0.06	0.09	-0.69	.494
	Internalizing	Constant	66.79	3.59	18.63	.000
		G3 Internalizing	0.24	0.02	11.18	.000
		Demographics	4.57	1.87	2.45	.015
		Neighborhood	3.15	1.60	1.97	.050
		Demo x Neighborhood	-1.09	0.90	-1.21	.227
	Externalizing	Constant	56.91	3.11	18.27	.000
		G3 Externalizing	0.32	0.02	17.61	.000
		Demographics	4.26	1.70	2.50	.012
		Neighborhood	2.34	1.44	1.62	.105
		Demo x Neighborhood	-0.02	0.80	-0.02	.981
	Social	Constant	-0.71	0.37	-1.89	.059
		Child Sex	0.88	0.10	9.15	.000
		G3 Social	0.80	0.03	23.32	.000
		Demographics	-0.22	0.21	-1.04	.301
		Neighborhood	-0.05	0.19	-0.24	.809
		Demo x Neighborhood	-0.07	0.10	-0.71	.477

Interaction Effect	**Outcome**	**Variable Entry**	**Unst. B**	**Std. Error**	***t* value**	***p* value**
Neighborhood x Physical Home	Academics	Constant	0.51	0.36	1.41	.159
		Child Sex	0.14	0.10	1.46	.145
		G3 Academics	0.78	0.02	39.96	.000
		Neighborhood	-0.19	0.18	-1.07	.288
		Physical Home	-0.05	0.17	-0.29	.774
		Neighborhood x Phys Home	-0.09	0.08	-1.10	.272
	Internalizing	Constant	66.74	3.74	17.83	.000
		G3 Internalizing	0.24	0.02	11.17	.000
		Neighborhood	3.81	1.73	2.20	.029
		Physical Home	3.28	1.71	1.91	.058
		Neighborhood x Phys Home	-0.96	0.89	-1.09	.280
	Externalizing	Constant	55.90	3.43	16.31	.000
		G3 Externalizing	0.33	0.02	17.62	.000
		Neighborhood	2.67	1.62	1.65	.102
		Physical Home	3.48	1.62	2.15	.035
		Neighborhood x Phys Home	0.17	0.83	0.20	.843
	Social	Constant	-0.87	0.40	-2.20	.029
		Child Sex	0.88	0.10	9.20	.000
		G3 Social	0.81	0.03	23.69	.000
		Neighborhood	0.03	0.20	0.17	.868
		Physical Home	-0.04	0.19	-0.21	.835
		Neighborhood x Phys Home	-0.14	0.09	-1.47	.144

Interaction Effect	**Outcome**	**Variable Entry**	**Unst. B**	**Std. Error**	***t* value**	***p* value**
Neighborhood x Emotional Home	Academics	Constant	0.77	0.34	2.28	.023
		Child Sex	0.14	0.10	1.46	.146
		G3 Academics	0.80	0.02	41.48	.000
		Neighborhood	-0.45	0.17	-2.60	.010
		Emotional Home	-0.16	0.17	-0.96	.337
		Neighborhood x Emot Home	0.02	0.09	0.22	.830
	Internalizing	Constant	68.15	3.57	19.08	.000
		G3 Internalizing	0.23	0.02	10.87	.000
		Neighborhood	2.38	1.69	1.41	.161
		Emotional Home	3.17	1.76	1.80	.074
		Neighborhood x Emot Home	-0.14	0.94	-0.15	.883
	Externalizing	Constant	55.68	3.13	17.81	.000
		G3 Externalizing	0.32	0.02	17.25	.000
		Neighborhood	3.99	1.47	2.72	.007
		Emotional Home	3.29	1.51	2.18	.030
		Neighborhood x Emot Home	-0.04	0.79	-0.06	.955
	Social	Constant	-0.92	0.36	-2.53	.012
		Child Sex	0.89	0.10	9.21	.000
		G3 Social	0.83	0.04	23.56	.000
		Neighborhood	-0.14	0.18	-0.77	.440
		Emotional Home	0.06	0.19	0.32	.750
		Neighborhood x Emot Home	-0.10	0.10	1.04	.297
Physical Home x School	Academics	Constant	0.90	0.33	2.77	.006
		Child Sex	0.15	0.10	1.53	.127
		G3 Academics	0.79	0.02	40.63	.000
		Physical Home	-0.51	0.16	-3.11	.002
		School	-0.37	0.16	-2.25	.025
		Phys Home x School	0.13	0.08	1.55	.123
Emotional Home x School	Academics	Constant	0.25	0.34	0.75	.454
		Child Sex	0.15	0.10	1.61	.108
		G3 Academics	0.81	0.02	42.47	.000
		Emotional Home	-0.13	0.17	-0.74	.463
		School	-0.14	0.17	-0.83	.411
		Emot Home x School	-0.02	0.09	-0.16	.871

Note. Degrees of freedom for all models is 1077.